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The impact of anti-smoking information scanning via social media on actual anti-smoking behaviors in China

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Doutoramento em Ciências da Comunicação

Orientadores(as):
Professora Auxiliar (com Agregação), Rita Espanha
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I am still learning

— *Michelangelo*

at age 87

Acknowledgement

My doctoral career is a kind of serendipitous adventure, unpredictable and with a bit of luck. I had started a career, partly, to understand and deal rationally with the realities of a life in science. I am thankful for all the difficulties and challenges I encountered in the last few years that made me the best version of myself.

I want to express my sincere appreciation to my mentor, Professor Rita Espanha, for nearly six years of guidance, patience, assistance, and encouragement. Her wisdom, creativity, and enthusiasm have continued to inspire me. She has created an environment where I feel the freedom to peregrinate, image, and express my thoughts. Thank you for always being there.

The deepest gratitude goes to my parents for their continuous motivation during my life journey. They have always respected and supported me unconditionally. I would like to extend my special thanks to my husband. His caring love and steadfast support bring me an unwavering source of security and comfort, making everything worthwhile. Last but not least, I am indebted to all my dearest friends who have been accompanied me when I was struggling. They made me believe, perhaps I, also, could join the ranks of these polymaths, who strode into the densest thicket of emotional, scientific, and spiritual problems and found, or carved, ways out.

Wish we can
Keep passionate
Walk in truth
Revel in everyday, warts and all

Resumo

Ao longo do século passado, o consumo de tabaco tornou-se uma preocupação pública crescente em todo o mundo. Juntamente com os avanços das tecnologias móveis, existe uma necessidade reconhecida de divulgar mensagens de saúde para um público mais amplo por meio de várias plataformas de redes sociais, com o fim de melhorar os resultados em saúde pública. Consequentemente, têm sido realizadas pesquisas substanciais sobre o papel das plataformas online em campanhas antitabagismo. Pesquisas anteriores indicaram associações potenciais entre a aquisição de informações de saúde online e os comportamentos de saúde dos utilizadores de Internet. Consequentemente, esta tese inclui três estudos base com o objetivo de determinar os ambientes de informação antitabagismo nas redes sociais na China, bem como explorar e explicar como a amplitude de informações antitabagismo via redes sociais exerce influência sobre os comportamentos antitabagismo reais.

O primeiro estudo recrutou 11,586 posts antitabagismo de contas oficiais do WeChat, TikTok e plataforma de Sina microblog para categorizar seus temas, tipo de conteúdo, tipo de media e tipo de comunicador por meio de análise de conteúdo. Além disso, foram conduzidos testes qui-quadrado para descrever quantitativamente as diferenças nas características dos posts antitabagismo entre três plataformas. Este estudo conclui que os posts sobre os perigos de fumar foram os mais prevalentes nas três plataformas. Além disso, os posts antitabagismo no WeChat, na sua maioria disseminados por plataformas de saúde e media, eram mais sobre dicas e formas eficazes de parar de fumar, fornecendo mais suporte informativo e conteúdo baseado em conhecimento especializado. A plataforma de microblog Sina, na qual contas individuais e governamentais colocam posts com mais frequência, forneceu mais informações antitabagismo sobre notícias e atividades sociais e ofereceu mais apoio emocional e conteúdo baseado em experiências. A maioria das informações antitabagismo no TikTok foi fornecida por contas de saúde e media que tratavam mais sobre cigarros eletrónicos e continham mais suporte informativo e conteúdo com base em experiência e conhecimento.

O segundo estudo foi realizado para explorar a associação de exploração de informações antitabagismo e comportamentos antitabagismo de utilizadores de redes sociais com base na Teoria do Comportamento Planeado (TCP). Uma pesquisa online forneceu dados quantitativos a partir de 806 participantes. Ao realizar a modelagem de equação estrutural com mínimos quadrados parciais (PLS-SEM) e a análise de multigrupos, os resultados indicaram que a exploração de informações antitabagismo via redes sociais tem influência positiva sobre os comportamentos antitabagismo, moldando as normas subjetivas, atitudes comportamentais e autoeficácia de um indivíduo. As análises de multigrupos revelaram que as diferenças no efeito direto e total da exploração de informações antitabagismo entre os subgrupos não foram significativas. Análises post-hoc encontraram evidências de que existem duas variáveis

demográficas relacionadas à aquisição não intencional de informações antitabagismo dos fumantes e não fumantes, incluindo renda e idade.

O terceiro estudo pretendeu determinar até que ponto os determinantes sociais e individuais afetaram a exploraçã de informações antitabagismo de utilizadores de redes sociais, bem como verificar como a digitalização de informações antitabagismo via redes sociais afetou os comportamentos antitabagismo com base no modelo de crenças em saúde (HBM) e no modelo de influência estrutural da comunicação (SIM). Um total de 921 de utilizadores de redes sociais foi recrutado através da distribuição de dois questionários online. Ao utilizar a modelagem de equação estrutural com mínimos quadrados parciais (PLS-SEM), foi demonstrado de forma conclusiva que a exploração e pesquisa de informações antitabagismo está positivamente associada a comportamentos antitabagistas de fumadores e não fumadores, influenciando suas perceções e atitudes. Entre os fumadores, as barreiras percebidas, a gravidade percebida e a autoeficácia foram mediadores significativos, enquanto entre os não fumadores, a autoeficácia foi o único mediador significativo conectando comportamentos antitabagistas e a pesquisa de informações antitabagismo via redes sociais. Ao usar a análise de multigrupo, foi demonstrado que a maioria das diferenças nos coeficientes de caminho entre os subgrupos populacionais não era evidente, especialmente o efeito total da pesquisa de informações antitabagismo sobre os comportamentos antitabagistas não foi mediado por determinantes sociais e individuais. Ao realizar a análise de comparações e regressão, também foram identificadas as características do tabagismo dos utilizadores de redes sociais e do público-alvo de três plataformas online. Nesse aspeto, os utilizadores de redes sociais do sexo masculino, mais jovens ou com maior rendimento mensal têm maior probabilidade de serem fumadores diários. E utilizadores de redes sociais do sexo feminino e mais jovens tendem a usar cigarro eletrónico. Além disso, utilizadores de redes sociais do sexo masculino e mais velhos têm maior probabilidade de serem fumadores viciados. Os resultados também indicaram que os fumadores que relataram usar cigarros eletrónicos com frequência, ou ter maior rendimento mensal ou maior nível educacional tendem a confiar no microblog Sina. Os não fumadores, especialmente aqueles com menor rendimento mensal ou menor nível educacional, preferem as contas oficiais do WeChat. E os fumadores que relataram usar cigarros comuns e os não fumadores que relataram rendimento médio tendem a usar o TikTok.

Fica evidentemente claro, a partir dos resultados, que uma grande quantidade de informações antitabagismo tem sido disseminada por meio de diferentes plataformas online em todos os tipos de formas, melhorando assim as perceções e promovendo comportamentos antitabagistas, não apenas entre a população em geral, mas também entre grupos carenciados. Os resultados apresentados nesta tese também adicionam uma compreensão do ambiente de informação da educação sobre o tabagismo online e representam um avanço para o desenvolvimento de estratégias de segmentação de mensagens. Esta tese pode, assim, ser importante para investigadores da área da comunicação e profissionais de saúde que desejam projetar mensagens antitabagistas mais persuasivas direcionadas a diferentes plataformas online e subgrupos populacionais. Mais importante, ter em consideração a especificidade de género e as

características culturais da sociedade chinesa aumentaria a eficácia das campanhas antitabagismo nas redes sociais. E esforços contínuos são necessários para entregar mensagens antitabagistas mais compreensíveis, atraentes e memorizáveis por meio das redes sociais, com foco no efeito de novidade, efeito de teto, fadiga de mensagens e apelo ao medo.

Palavras-chave: Plataformas de redes sociais; Amplitude de informações; Comportamentos antitabagismo; Estratégias de segmentação de mensagens; Utilizadores Chineses de redes sociais; Uso do tabaco

Abstract

Over the past century, tobacco epidemic has become a growing public concern worldwide. Along with the advancements of mobile technologies, there is a recognized need for disseminating health messages to a broader audience through various social media platforms in order to improve public health outcomes. Consequently, there has been substantial research undertaken on the role of social media platforms in anti-smoking campaigns. And previous research has indicated potential associations between online health information acquisition and health behaviors of internet users. Consequently, this dissertation includes three main studies with the aim of determining the anti-smoking information environments of social media in China, as well as exploring and explaining how anti-smoking information scanning via social media exerts influence on actual anti-smoking behaviors.

The first study recruited 11,586 anti-smoking posts from WeChat official accounts, TikTok and Sina microblog platform to categorize its themes, content type, media type and communicator type by using content analysis. Also, Chi-square tests were conducted in order to quantitively describe the differences in characteristics of anti-smoking posts among three platforms. This study concludes that the posts regarding the hazards of smoking were the most prevalent on all three platforms. Furthermore, anti-smoking posts on WeChat that most of them were delivered by health and media accounts were more about tips and effective ways of smoking cessation, providing more informational support and expertise-based content. Sina microblog platform where individual and governmental accounts posted more frequently delivered more anti-smoking information about social news and activities and offered more emotional support and experience-based content. Most of anti-smoking information on TikTok were delivered by health and media accounts that were more about e-cigarette and contained more informational support and content based on both experience and expertise.

The second study was undertaken to explore the association of anti-smoking information scanning and anti-smoking behaviors of social media users based on the theory of planned behavior model. An online survey provided quantitative data from 806 participants. By performing the partial least squares structural equation modeling (PLS-SEM) and multigroup analysis, the findings indicated that anti-smoking information scanning via social media has positive influence on anti-smoking behaviors by shaping an individual's subjective norms, behavioral attitudes and self-efficacy. Multigroup analyses revealed that the differences in direct and total effect of anti-smoking information scanning across subgroups were not significant. Post-hoc analyses found the evidence that there have two demographic variables related to scanning information acquisition of the smokers and non-smokers, including income and age.

The third study intended to determine the extent to which social and individual determinants affected anti-smoking information scanning of social media users, as well as ascertaining how anti-smoking information scanning via social media affected anti-smoking behaviors based on the health belief model and the structural influence model of communication. A total of 921 social media users was recruited by distributing two questionnaires online. By employing the partial least squares structural equation modeling (PLS-SEM), it has been conclusively shown that anti-smoking information scanning is positively associated with anti-smoking behaviors of both smokers and non-smokers through influencing their perceptions and attitudes. Among smokers, perceived barriers, perceived severity and self-efficacy were found to be significant mediators, whereas among non-smokers, self-efficacy was the only significant mediator connecting anti-smoking behaviors and anti-smoking information scanning via social media. By using multigroup analysis, it has been shown that most of differences in path coefficients among population subgroups were not evident, especially the total effect of anti-smoking information scanning on anti-smoking behaviors was not mediated by social and individual determinants. By conducting comparison and regression analysis, the smoking characteristics of social media users and target audience of three social media platforms were identified as well. In this aspect, social media users who are male, younger or have higher monthly income are more likely to be everyday smokers. And female and younger social media users tend to use e-cigarette. Furthermore, male and elder social media users are more likely to be addicted smokers. Additionally, the findings indicated that smokers reported using e-cigarette frequently, or having higher monthly income or higher educational attainment tend to rely on Sina microblog. Non-smokers, especially those with lower monthly income or lower educational level prefer WeChat official accounts. And smokers who reported using regular cigarette and non-smokers who reported middle income tend to use TikTok.

It is evidently clear from the findings that a vast amount of anti-smoking information has been disseminating via different social media platforms in all kinds of forms, thereby improving perceptions and promoting anti-smoking behaviors not only among general populations, but also among underserved groups. The findings presented in this dissertation also add our understanding of information environment of tobacco education on social media and then represent further steps towards developing message segmentation strategies. This dissertation should, therefore, be of value to both communication researchers and health practitioners wishing to design more persuasive anti-smoking messages targeting to different social media platforms and population subgroups. More importantly, giving more consideration to gender specificity and cultural characteristics within Chinese society would enhance effectiveness of anti-smoking campaigns on social media. And continued efforts are needed to deliver more understandable, attractive and memorable anti-smoking messages via social media, focusing on novelty effect, ceiling effect, messages fatigue and fear appeal as well.

Keywords: Social media; Information scanning; Anti-smoking behaviors; Segmentation strategies; Chinese social media users; Tobacco use

General Index

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List of abbreviations and acronyms

AVE: Average variance extracted

BA: Behavioral attitudes towards anti-smoking

BE: Behavioral economics

BQS-SAT: Barriers to quitting smoking in substance abuse treatment questionnaire

CDC： Centers for Disease Control and Prevention

CISB: Cancer information seeking behaviors

CPD: Cigarettes smoked per day

CR: Composite reliability

FCTC： Framework Convention on Tobacco Control

FTND: Fagerstrom test for nicotine dependence

GATS： Global adult tobacco survey

GBD： Global Burden of Disease

GYTS： Global youth tobacco survey

HBCTs: Health behavior change theories

HBM： Health belief model

HISB: Health information seeking behaviors

HRI: Health-related information

HTMT: Heterotrait-Monotrait criterion

ICA: International Communication Association

ICTs: Information and communication technologies

IN: Anti-smoking information scanning

MGA: Multigroup analysis

MICOM: Measurement invariance of composite models

OLS: Ordinary least square

One-way ANOVA: One-way analysis of variance

PBA: Perceived barrier

PBE: Perceived benefit

PLS-SEM: Partial least squares structural equation modelling

PSE: Perceived severity

PSU: Perceived susceptibility

RISP: Risk information seeking and processing model

SADs：Smoking-attributable deaths

SASEQ: Smoking abstinence self-efficacy questionnaire

SCT: Social cognitive theory

SD: Standard deviation

SDT: Self-determination theory

SE: Self-efficacy

SHDPP: Stanford Heart Disease Prevention Program

SIM: Structural influence model of communication

SM: Social media

SN: Subjective norm

SPSS: Statistical Product Service Solutions

TPB: Theory of planned behavior model

TRA: Theory of reasoned action

TTF: First cigarettes after waking up

TTM: Transtheoretical model

VIF: Variance inflation factors

WHO：World Health Organization

CHAPTER 1

Introduction

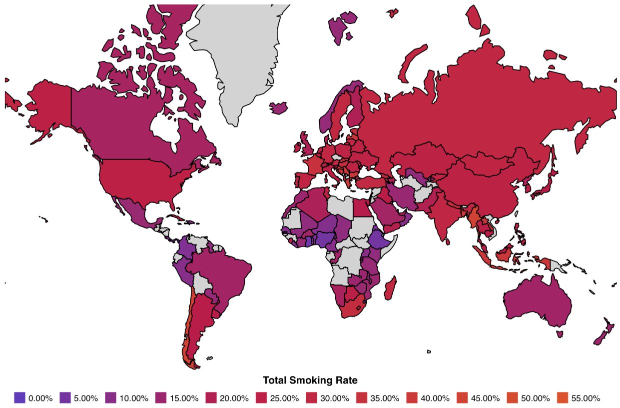
1.1. Research Background

1.1.1. The global prevalence of tobacco use

1) The worldwide panorama

Over the past century, the tobacco epidemic has been a major public health threat that has led to around 100 million deaths worldwide (WHO, 2021). According to the report released by World Health Organization in July 2022, smoking has remained the second leading risk factor for preventable mortality since 1990. It is responsible for around 8.7 million deaths annually, while about 1.2 million deaths were attributed to second-hand smoke exposure.

In the last few decades, cigarette smoking, cigars, waterpipe tobacco, and other smokeless products have led to tobacco-related illnesses, such as cardiovascular disease, lung cancer, respiratory diseases, and dental diseases. Until 2021, the total number of smokers aged 15 years and older reached more than 1.3 billion worldwide. In this regard, what stands out in Graph 1.1 is the remarkable smoking prevalence in the world, particularly in South-east Asian (N= 432 million), the Western Pacific (N= 406 million), and European (N= 190 million). As a result, there will be an estimated 1270 million smokers by 2025 around the world, accompanying the increased number of smoking-attributable deaths (SADs) and a greater incidence of tobacco-caused diseases in the general population (Jafari et al., 2021).



Graph 1.1. Total smoking rates by country 2021

(Source: Smoking Rates by Country 2023, n.d.)

According to the guidelines released by the WHO Framework Convention on Tobacco Control (WHO FCTC), six MPOWER measures have been introduced with the aim of implementing tobacco control as follows: a) regulating tobacco use and formulating prevention policies; b) protecting people from exposure to second-hand smoke and tobacco smoke; c) offering services and advice to help people to quit smoking; d) boosting education about the health hazards of tobacco use; e) raising cigarettes taxes and f) prohibiting tobacco advertising and promotion (Levy et al., 2018). In a global context, MPOWER measures have been adopted by more and more countries that up to now, over 5.3 billion people have been covered by at least one higher level MPOWER measure, resulting in a decrease in current tobacco smoking (Husain et al., 2021; WHO, 2021). At the same time, recent trends have heightened the need for implementing more legislative measures to monitor electronic nicotine delivery systems (ENDS).

As can be seen from the data in Figure 1.1 below, focusing on the period from 2000 to 2020, inspiringly, there has been a dramatic reduction in the smoking prevalence rates among people over 15 years due to the steady progress of tobacco education delivered by countries worldwide. Nevertheless, it has to exert more effort to achieve the global targets that the smoking prevalence is projected to reduce to 20.9% (global), 25.1% (in South-East Asian), and 25.2% (in China). In particular, since the outbreak of the Covid-19 pandemic in 2020, several projects have been launched to strengthen tobacco cessation measures given the increasing concerns about the impact of tobacco use on Covid-19 infection, such as the Access Initiative for Quitting tobacco and the Regional Action Plan for Tobacco Control in the Western Pacific. (WHO And Partners to Help More Than 1 Billion People Quit Tobacco to Reduce Risk of COVID-19, 2020; WPRO IRIS, n.d.). However, greater stress and less access to prior coping strategies have become the key triggers for smoking during the pandemic (Meacham et al., 2021; Patanavanich & Glantz, 2021).

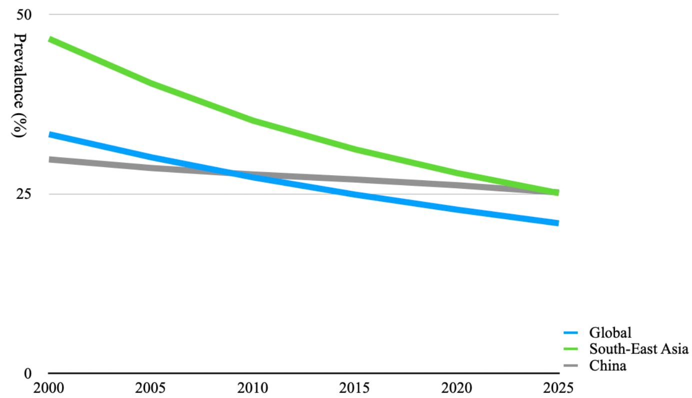


Figure 1.1. Trends in the prevalence of current tobacco use among people aged ≥15 years (2000-2025) (Source: WHO Global Report on Trends in Prevalence of Tobacco Use 2000-2025, Third Edition, 2019)

2) Trends in tobacco smoking in China

In line with the global adult tobacco survey (GATS), until the end of 2018, there are more than 300 million current tobacco smokers in China, approximately accounting for one-third of the world’s total. Statistically, the number of deaths caused by the tobacco epidemic in China occupied nearly 27.5% of the world’s, amounting to 2.2 million per year, and this number is forecast to reach over three million by 2050. In addition, the report released by Global Burden of Disease (GBD) in 2017 represents that 21.03% of the total deaths in China are due to smoking, and over 23% of cancer is attributed to tobacco use. Regarding cigarette consumption, 41.9% of all cigarettes globally were smoked by Chinese smokers in 2016, ranking first in the world (Global Tobacco Control Information & Statistics I Tobacco Atlas, n.d.). Also, China has always been the largest manufacturer of cigarettes worldwide, and its production currently accounts for half of the world's total (Flenaugh, 2019). Statistics showed that 50.9% of Chinese adults and 57.2% of Chinese youth (aged 13-15) were exposed to second-hand smoke in 2018, and this data has barely changed in past years (Leng & Wu, 2020). From 2010 to 2018, although the percentage of smokers who planned to quit smoking significantly increased from 14.4% to 19.8%, no statistically significant difference in overall current tobacco use was found in China (28.1% in 2010 and 26.6% in 2018) (Figure 1.1). As one of the most important national strategies released by the Chinese government, the primary goal of the Healthy China 2030 strategy is to reduce smoking prevalence to below 20% by the end of 2030 (Fong & Jiang, 2020). Obviously, combating the tobacco epidemic continues to be a considerable challenge in China’s health promotion.

Regarding the profile of Chinese smokers, previous research focusing on the association of gender and smoking behaviors has found that men, especially those with lower education levels, were more likely to be current smokers than women, accounting for almost half of China’s total smokers. For men, being unmarried and unemployed decreased the odds of being a current smoker, while for women, those who were employed and married had lower smoking prevalence. And men were generally considered to consume more cigarettes per day than women (Zhang, G et al., 2022). In line with the China National Health Survey and the global youth tobacco survey (GYTS), the smoking rates of chinses adolescents (aged 15-24 years) had steadily risen from 8.3% in 2003 to 18.6% in 2018, and the smoking rates of male adolescents reached 34%. Notably, it is predicted that the number of teenage smokers (aged 15-24 years) will continue its upward trend in China, especially among female adolescents (Liu, S et al., 2020; Xiao & Wang, 2019).

The Chinese government has paid ongoing attention to tobacco control in the past five years, including establishing cessation clinics, providing easier access to cessation programs, increasing tobacco taxation, and implementing smoke-free laws (Parascandola & Xiao, 2019; Xue, 2020). In a striking move, the Chinese government has announced a series of strictest policies in history that bans tobacco and e-cigarette use in public places and prohibits tobacco and e-cigarette advertising on mass media. One of the significant steps was the release of the ban that smoking has been prohibited in public and working places since 2011. Besides, many subnational governments issued smoking control ordinances in compliance with the FCTC guidelines in the following years. Similarly, questions have been raised about the detrimental impacts of prolonged tobacco use in the context of the COVID-19 pandemic in China (Sun et al., 2020). Although recent trends in tobacco control have led to a proliferation of anti-smoking campaigns across mass media, more coping strategies still need to be implemented to promote smoking cessation and prevent new smokers in China (Qian et al., 2018).

1.1.2 The popularization of social media

Overall, there is a clear trend of increasing social media users both in China and the world, given the advent of mobile technologies. The report of Global Digital 2021 presents that there have over 4.95 billion people using mobile Internet around the world, with the Internet penetration rate growing to 59%. Results of the report revealed that 93.4% of Internet users access social media platforms where they spend more than 2 hours 30 minutes a day on average. Until January 2022, the number of social media users worldwide has passed 4.62 billion, accounting for 58.4% of the world's population (Figure 1.2). Mainly, 74.8% of the social media users are thirteen years of age or older, and 53.9% of the social media users are male.

The Digital China 2020 revealed that social media has emerged as a powerful communication tool and primary information source and that the total number of Chinese social media users reached over one billion, approximately equivalent to 72% of China's total population (Digital 2020: China &Mdash; DataReportal – Global Digital Insights, 2020). Similarly, coupled with the substantial growth of the Internet penetration rate, the total number of Chinese Internet users has grown by 3.1% between 2019 and 2020, reaching over 854.5 million. What is more, the average time a Chinese Internet user spends online daily is around five hours and fifty minutes, far higher than the global average. Regarding Chinese social media behaviors, 98% of them use social media platforms for messaging services, and each Chinese user registered over 9.3 social media accounts. During the COVID-19 pandemic, 44% of the respondents showed that they rely more on digital platforms to search for health information. Around 50% of Chinese Internet users report spending more time on social media platforms (Coronavirus Impact: Global In-home Media Consumption by Country 2020 | Statista, n.d.). In view of all that has been mentioned so far, social media is fast becoming a critical instrument for generating, obtaining, and exchanging digital content in China and the world. Figure 1.3 displays the monthly active users of five popular social media platforms in China, such as WeChat, Sina microblog, TikTok, Kuai Shou, and Tencent QQ. Indeed, substantial growth in monthly active users of these platforms has been observed since 2016.

With its countless features, WeChat has become more advanced and powerful and appeals to over 90% of Chinese Internet users in recent years (Zhang, X. et al., 2021). Considering the most prevalent social media platforms in China, WeChat was, known as Chinses WhatsApp, which integrates diverse functionalities such as instant messaging, voice and video calling, mobile pay, money transfer, multipurpose social services, online shopping, healthcare, and so on. Compared with the other social media platforms, WeChat has provided a more private environment based on users' relationships. Until the end of 2020, the total number of WeChat users has reached around 1.2 billion, with over 360 million users subscribing to at least one official account on WeChat (Team, 2023). One of the special functions of WeChat is that both individual users and organizations or businesses can register an official account to deliver notifications, messages, and posts to their subscribers. In turn, WeChat users can follow any of those accounts and receive and interact with these multimedia posts (Guo et al., 2017). Statistics show that 70% of WeChat users subscribed to around twenty official accounts that offer potential opportunities for disseminating a variety of tailored and customized information. From this perspective, prior studies have pointed out that WeChat official accounts were equivalent to Facebook pages (Carvajal-Miranda et al., 2020).

The second most commonly used social media platform in China is Sina microblog, known as Chinese Twitter. In other words, the Sina microblog has been considered an information-driven online social networking site. A variety of its functions is based on a follower-followed network where users can post, retweet, share, and comment (Guo, Z et al., 2013). Unlike WeChat, Sina micro-blog is more visible, interactive, and open. As China's earliest and most popular microblogging system, the total number of active users continues to grow to more than 5.2 million by 2020. Given the increased digital needs for instant messaging and content production among Chinese Internet users, the Sina microblog plays a critical role in facilitating information propagation and influencing the emotional status of Chinese citizens (Yin et al., 2021).

Additionally, in the past five years, there has been a significant rise in the popularity of TikTok in China and worldwide, with around 5.51 million people using it by the end of 2020. This platform focuses on sharing short-form videos where young smartphone users can rapidly interconnect and easily exchange user-generated content. In this commentary, initial evidence predicted that the number of global social media users would continue to increase in a few years, and there was no doubt that the widespread public engagement with user-oriented social media provides an avenue for creating and propagating vast information in a large scale (Carvajal-Miranda et al., 2020).

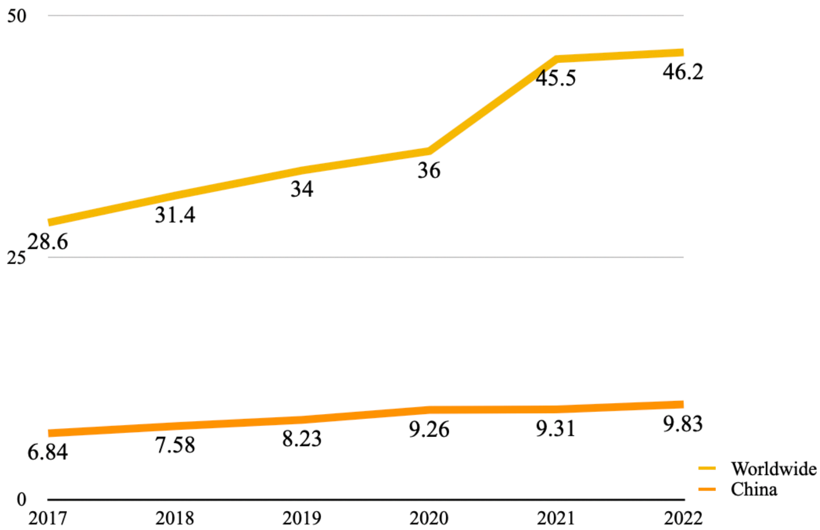


Figure 1.2. Number of social media users worldwide and in China (2017-2021) (in hundred million)

(Source: Digital 2021: Global Overview Report &Mdash; DataReportal – Global Digital Insights, 2021)

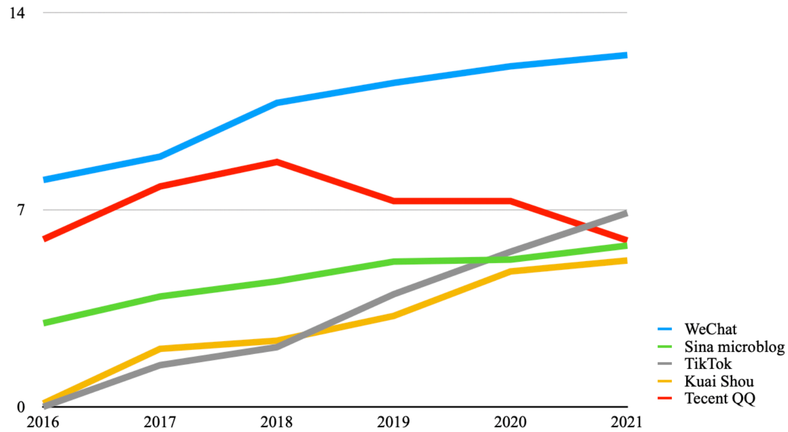


Figure 1.3. Monthly active users of five social media platforms in China (2016-2021)

(Source: Author created)

1.1.3. Health-related social media use

Along with the increased number of social media users, there has been a surge of interest in the theme of health-related social media users worldwide. The Global Strategy on Digital Health (2020-2025) emphasized the value of global collaboration in advancing digital technologies to achieve well-being goals, mitigating threats caused by mobile Internet use, and disseminating health information by implementing integrated strategies (WHO, 2020). In this regard, for example, according to the surveys conducted by Pew Research Center in 2014 and 2020, over half of Internet users searched health information across social media platforms in the past 12 months. Additionally, it is now well established from various studies that most elderly people and parents search for their health symptoms on social media. Similarly, over half of millennials follow healthcare professionals on social media and wish to interact with their doctors via social media (Bryan et al., 2020; Tennant et al., 2015).

Generally, with greater access to the Internet, social media has been utilized as interactive communication tools for health-related campaigns by patients, clinicians, health institutions, and scientists. Currently, running health activities via social media has increased sharply, for instance, the Centers for Disease Control and Prevention (CDC) launched a series of health campaigns in order to promote healthy living worldwide, such as *Tips from Former Smokers, Diabetes Awareness Campaign,* and *Hear Her Campaign* (CDC, 2023). Indeed, using social media in the public health field can boost health campaign engagement and elicit positive attitudes and behavior changes efficiently and effectively (Al-Dmour et al., 2020; Edney et al., 2018). In this commentary, up to now, social media-based health communication has become the major trend and a nascent field of research to raise public health awareness worldwide. Meanwhile, the ongoing spread of COVID-19 highlights the increased need to take full advantage of social media to address critical health issues as well (Chan et al., 2020).

Firstly, social media use by the general public for health-related reasons has enabled valuable possibilities for increasing the availability of educational information and sharing personal experiences on a broad range of topics (Moorhead et al., 2013; Saigal, 2019). Secondly, social media use by healthcare professionals for health purposes can be beneficial in facilitating the exchange of scientific outreach, monitoring and interacting with patients, combating misinformation, and promoting public behavioral changes (Dorje et al., 2019; Huo et al., 2019; Sharma et al., 2017). Thirdly, social media use by health institutions offers opportunities for quickly informing health policies widely and engaging the public, mobilizing resources, and understanding public concerns (Chen & Wang, 2021; Vandormael et al., 2020). Similarly, social media is also suitable for at-risk groups and chronic disease patients that can leverage its immediacy and interactivity to serve information needs and request peer support in a virtual community (Benetoli et al., 2018; Isip-Tan et al., 2020). In this aspect, for example, there is an increasing number of health campaigns delivered through social media for tobacco control, nutrition, mental health, and alcohol abuse (Jonhs et al., 2017). Notably, more and more anti-smoking public education campaigns, such as The Truth campaign, have been launched to increase quit rates and reduce tobacco use initiation (Kim, 2021). In the post-epidemic era, several scholars hold the view that the rapid growth of mobile social media has a considerable impact on public well-being and self-management in the future (Jazieh & Kozlakidis, 2020; Mendoza-Herrera et al., 2020).

Parallel to a continuous increase in mobile Internet penetration, a recent study revealed that the percentage of online health information seeking had reached 79% or even higher in China (Wang et al., 2021). Since 2015, aiming to mobilize sources and extend the coverage of public health services, the Chinese government has introduced a series of policies and regulations to strengthen cooperation between digital media and public health authorities (Ngai et al., 2020). The "Healthy China 2030" blueprint issued by the State Council in 2019 also focuses on leveraging the characteristics of new media to strengthen health education and advocate health policies (Goodchild & Zheng, 2019). Thus, the Accenture 2021 China Consumer Study showed that over 80% of Chinses consumers have used virtual health appointments or have experienced virtual consultation via social networking sites in the past year (Accenture China Consumer Study, 2021). Along with the extensive use of social media, the varieties of user-generated health knowledge and personal experiences have grown remarkably. In turn, social media has become the major health information source among Chinese adolescents (Di et al., 2015; Wu and Shen, 2021). Up to now, a tremendous number of health-related information and various health services are being delivered via different social media platforms that continuously impact public health decisions (Gong, & Verboord, 2020; Zhang et al., 2017). According to the report released by CBNDATA in 2019, the total reading volume of digital health messages has reached over 54 billion, with an increase of 60.7% over the prior year. Additionally, over 40% of medical professionals had enrolled in Sina microblog or WeChat official accounts to disseminate or discuss health knowledge (Zhou et al., 2020). Currently, TikTok also has been utilized by a majority of provincial-level health authorities for public health education (Zhu et al., 2020).

Regarding the anti-smoking campaigns harnessing social media platforms in China, for instance, the first applet called "Smoking cessation effectively (Chinese: Jie Yan You Dao) was launched by Beijing Chao-Yang Hospital in April 2021 on the WeChat platform with the aim of offering professional advice and online consultation, delivering smoking cessation interventions and promoting tobacco education online. In addition, the China Tobacco Control Media Campaign was initiated by the Ministry of Health on the Sina microblog to advocate for smoking prevention, propagate the health consequences of tobacco use, and encourage smokers to quit smoking (Jiang & Beaudoin, 2016).

1.2. Issues and research objects

1.2.1. Research questions and objectives

Based on the described conditions above, the immense popularity of health-related social media uses created numerous paths for addressing public health concerns, such as satisfying informational or emotional needs by providing more convenient information sources and social support groups, reducing health inequalities, and connecting health professionals with patients (Niu et al., 2021). Along with the rapid growth of smoking prevalence, social media campaigns have been created to deliver health promotion on tobacco control as well. In this regard, prior studies have recognized that reducing youth initiation and increasing quit attempts have become two crucial goals for managing the substantial growth of premature deaths caused by the tobacco epidemic worldwide (Carson-Chahhoud et al., 2017; Jha, 2009; Yu et al., 2015). Undoubtedly, exposure to anti-smoking information during the routine use of social media has a remarkable impact on the health decisions of smokers and non-smokers (Bala, 2017; Baskerville et al., 2015). In this context, the central research question of this dissertation is how information scanning behaviors on social media are associated with anti-smoking behaviors of social media users in China. In other words, the overall aims of the current dissertation were to develop an understanding of the characteristics of anti-smoking information on social media and assess the motivations behind the actual anti-smoking behaviors. From this perspective, the present dissertation includes three studies to remedy three main research questions as follows:

Study 1: Content analysis of anti-smoking-themed posts on social media platforms in China

1º Research question: What anti-smoking information has been disseminated through social media in China?

Objective 1: Characterize the main themes and core topics of anti-smoking posts delivered via social media platforms and determine which is more prevalent.

Objective 2: Demonstrate the differences in characteristics of anti-smoking posts among different platforms, including communicators, media type, and content type.

Study 2: The impact of anti-smoking information scanning on anti-smoking behaviors of social media users in China: based on the TPB model

2º Research question: How anti-smoking information scanning on social media platforms exerts influence on anti-smoking behaviors of smokers and non-smokers, based on the theory of planned behavior (TPB) model?

Objective 1: Validate the TPB model in the Chinese context and explore the significant mediators between scanning information acquisition and anti-smoking behaviors.

Objective 2: Assess how path coefficients vary between smokers and non-smokers.

Study 3: Passive anti-smoking information acquisition via social media and anti-smoking behaviors in China: based on HBM and SIM model

3º Research question: How anti-smoking information scanning on social media platforms exerts influence on anti-smoking behaviors of smokers and non-smokers, based on the health belief model (HBM) and the structural influence model of communication (SIM)

Objective 1: Ascertain the smoking characteristics of social media users and describe and compare the social media use between smokers and non-smokers.

Objective 2: Examine how anti-smoking information scanning behaviors on social media vary among different social groups and investigate which social and individual determinants affect anti-smoking information scanning of social media users.

Objective 3: Explore the influence of anti-smoking information scanning via social media based on the health belief model and identify the predictors for anti-smoking behaviors of smokers and non-smokers, respectively.

Objective 4: Assess whether mediators and path coefficients differ among the population subgroups.

1.2.2. Overview of the methodological approaches

Considering the research questions mentioned above, this dissertation consists of three central studies that employed a quantitative approach and implemented the research progress as follows:

The main definitions, knowledge gap, theoretical framework, and hypotheses were put forward to begin this process based on certain research objectives. In general, it is necessary to clarify critical concepts under three research domains, including information behaviors, health behaviors, and social media communication (Figure 1.4). With the intent to develop a more comprehensive literature review, the literature search was conducted using the following search terms displayed in Table 1.1 through Google Scholar, Web of Science, and CNKI.

It will then go on to the pilot study to investigate which social media platforms have to be considered in this research. Next, both content analysis and questionnaire design were based on the pilot study's results and conclusions derived from previous studies. Therefore, the methodological approaches taken in the three studies are a quantitative methodology, with data being gathered by Python programming scripts and questionnaire distribution. Among current health communication research, the quantitative research was adopted for characterizing digital health content or identifying key influencers of behavioral changes from different perspectives (Ngenye& Kreps, 2020). To be sure, carrying out quantitative analyses has become key to providing a rounded, detailed illustration of the effectiveness of health campaigns via social media (Regnault et al.,2018).

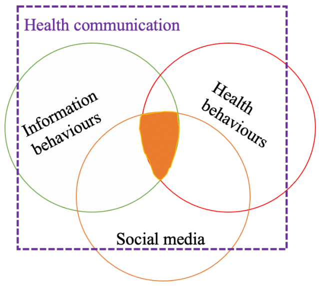


Figure 1.4. Three dimensions of literature review communication behaviors

(Source: Author created)

Table 1.1. Search terms

Information behaviors	**Health communication**	**Social media**
Information seeking	Smoking cessation outcomes	New media/digital media
Information scanning	Anti-smoking-related campaigns	WeChat/Sina microblog/ TikTok
Information engagement	Smoking cessation/anti-smoking attitudes, beliefs, and behaviors	YouTube/Facebook/Instagram
	Smoking-related information	(Re)Tweet/Post

(Source: Author created)

The first study, which was driven by the first research question, focused on gaining a detailed understanding of the characteristics of digital content relevant to anti-smoking. Using Python programming scripts, this study recruited anti-smoking posts from WeChat, TikTok, and Sina microblog platforms. After data cleaning, thematic analysis was adopted to illuminate the main themes and topic categories of information analyzed. Then, Chi-square tests were employed to identify the differences among social media platforms in terms of content type, format type, and information sources.

The second and third studies were driven by the second and third research questions, respectively. Firstly, data for two studies was collected by distributing two questionnaires online. One questionnaire was designed based on the theory of planned behavior model, and the other questionnaire was in accordance with the combination of the health belief model and the structural influence model of communication. In general, both studies performed partial least squares structural equation modeling using Smart PLS 3.3 to validate theoretical models and test proposed hypotheses. Similarly, multigroup analysis was conducted to determine the differences in path coefficients among subgroups. In fact, the third study employed more approaches to investigate the relationship between individual determinants and scanning information acquisition, as well as discussing the participants' social media use and smoking characteristics. These approaches in the third study include one-way analysis of variance test (ANOVA), Chi-square tests, and regression analysis.

1.2.3. Thesis structure

This dissertation is composed of three central studies corresponding to the three research questions mentioned above, respectively. The overall structure takes the form of seven chapters. It has been organized in the following way:

Chapter 1 contextualizes the research by providing background information on the tobacco epidemic, the popularization of social media, and health-related social media users worldwide. Notably, this section attempted to give an overview of current trends in smoking prevalence, the profile of Chinese smokers, and social media users worldwide. It will then go on to present the starting points and critical research questions that the present dissertation will address. In addition, this chapter also summarizes the methodologies used in this dissertation.

Chapter 2 refers to the literature review. This chapter is divided into five sections that offer a more detailed summarization of the main theories and principal findings from prior studies. Regarding social media communication, this section stated the definitions of social media and also tied together the common discussions about communication behaviors on social media platforms, including information scanning, information seeking, and engagement behaviors. In particular, this part included a comparison of the similarities and differences between information scanning and information seeking. In addition, this section also summarizes the principle findings of the digital divide. Regarding health communication, this part begins with the recent history of health communication. It is also concerned with the definitions of health communication from three perspectives: health-related information, targeted audience, and central purposes. Then, the section gives a brief summary of the crucial concepts in the field of health communication, including health attitude, health outcomes, and health behaviors. The third section considered health information acquisition on social media. In this regard, this part ties together the theoretical and empirical strands to present the behavioral models, such as the health belief model and the theory of planned behavior model. The main issues covered in this section are as follows: a) convincing evidence of the negative and positive influence of online information scanning and information seeking; b) the differential impact of online information scanning and information seeking; c) the earlier findings showing the relationship of information behaviors and health behaviors, including the structural influence model of communication; and d) individual differences in online health information acquisition. The fourth section presents the findings of the prior studies regarding the impact of social media use on smoking-related behaviors from five perspectives, focusing on its delivering content, target audience, advantages, engagement level, and effectiveness evaluation. Finally, the fifth section summarizes this chapter, demonstrates the existing knowledge gap, and then illustrates the objectives of this dissertation again.

The third chapter to the fifth chapter proceeds as follows: Chapter 3 (Study 1): Content analysis of anti-smoking posts on social media in China; Chapter 4 (Study 2): The impact of anti-smoking information scanning on anti-smoking behaviors of social media users in China: based on TPB model; Chapter 5 (Study 3): Passive anti-smoking information acquisition via social media and anti-smoking behaviors in China: based on HBM and SIM model.

The third chapter is subdivided into two sections, including methods and results. Regarding methodology, this section deals with the fundamental concepts relevant to content analysis and the primary data acquisition process, coding procedure, and analytical strategies. And then, it presents the results of the first study, focusing on the volume characteristics and differences in terms of topic categories, communicator, media type, and content type.

Likewise, the fourth and fifth chapters are subdivided into three sections. After establishing the theoretical frameworks and proposing hypotheses according to previous studies, questionnaire distribution, measurement, and data analyses were demonstrated in detail. Furthermore, the results section of both studies presents the credibility and validity of the questionnaire. It then explores the relationship of key influencers and significant differences by implementing the partial least squares structural equation modeling (PLS-SEM) and multigroup analysis (MGA) through Smart PLS3.3. In other words, these chapters interpret the significant data to provide empirical evidence of a positive or negative correlation between anti-information scanning and anti-smoking behaviors. In addition, the post hoc analysis was conducted in the second study to explore whether the social and individual determinants are associated with anti-smoking information scanning of social media users and whether the total effects of anti-smoking information scanning vary among subgroups. In what follows, the results section of the third study also showed the social media use and smoking characteristics of respondents, as well as the association of anti-smoking information scanning with the social and individual variables of the participants

Chapter 6 gathered the main findings of three studies, addressing each of the research questions in turn. It is divided into three sections: a) Effectiveness evaluation of anti-smoking information scanning via social media: total effect, direct effect, and significant mediators; b) Differences in anti-smoking information scanning and proposed relationships and c) Social media communication strategies for anti-smoking campaigns. Overall, this chapter includes a discussion of the implication of the findings, explaining the unexpected outcomes and results in line with or contrary to previous studies.

The purpose of the final chapter is to reflect on the extent to which this study has investigated, including the main conclusions, limitations, strengths, and theoretical and practical implications of the current dissertation. This chapter will also throw up questions in need of further research work.

CHAPTER 2

Literature Review

2.1. Social media communication

2.1.1. Definitions of social media

Historically, the definition of social media has been a matter of ongoing discussion among communication scholars and marketing managers. Since the term “social media” was first used in 1994, widely varying definitions have emerged due to its rapid development and diverse applications (Aichner et al., 2020). Generally, social media (SM) can be defined as online spaces that involve non-directed peer-to-peer exchanges of user-generated information or personal experiences (Naslund, 2016; Pechmann et al., 2015). As the definition of social media varies among researchers, and it is often used interchangeably, and without precision, here, it is essential to clarify how the term is used in this dissertation.

Early studies have demonstrated that “social media” can be interchangeable with social networking (Hughes et al., 2012; Moorhead et al., 2013). Over the past two decades, social networking sites have turned into a specific type of social media, given major advances in digital technologies (Aichner & Jacob, 2015). To be sure, social media has been recognized as an umbrella term that contains different typologies depending on the characteristics and functions, including microblogging platforms of applications (e.g., Sina microblog, Twitter), social networking sites (e.g., Facebook), chat platforms (e.g., WhatsApp, WeChat), video-sharing platforms (e.g., TikTok, YouTube) and more (Aichner et al., 2020; Kapoor et al., 2018). Conclusively, it has been proposed that the advantages of microblogging platforms, social networking sites, and video-sharing platforms are that they enable individuals not only to generate content in a personal style or in a collective way but also to create a community by exchanging or commenting specific posts in a conversation style (Heinonen, 2011). Arguably, scholars have contended that online chat-based platforms have expanded the scope of mobile interpersonal connection and maintained individuals' networks by employing innovative technological affordances (Rui et al., 2019). Taking advantage of the commonalities mentioned above, prior studies have concluded that two foundations to distinguish social media are Web 2.0 technologies and the propagation of user-generated content (Lewis, 2009; Kaplan & Haenlein, 2010).

Due to its diverse functionalities, most research has emphasized the heterogeneous nature of social media. One is interactive nature, also regarded as social nature, and the other one is informational features, targeting online user-generated or entertainment-driven content (Eckert et al., 2018). In this way, researchers have begun to conceptualize social media by identifying all kinds of motives for choosing and involving in social media activities. On the one hand, the research to date has highlighted that the most common motive tied to social media use refers to creating and maintaining social networks through broadcasting (posting digital content) and browsing (passive involvement) based on the interactive nature of social media platforms (Frison & Eggermont, 2017; Rhee et al., 2021). On the other hand, within communication studies, the propagation of user-generated and entertainment-driven content has been regarded as the lifeblood of social media that individuals can obtain knowledge, thereby strengthening a sense of community (Laroche et al., 2012; Obar & Wildman, 2015). Additionally, it has been conclusively shown that social media's interactive nature refers to human-human interaction and human-computer interaction (Carr & Hayes, 2015).

According to a definition provided by Kaplan and Haenlein (2010), social media refers to a series of Web 2.0-based applications where users can create and exchange content and socialize with contacts. Similarly, Aichner and Jacob (2015) offer a similar definition in their research. Therefore, in the present dissertation, social media contains a variety of Internet-based applications that allow participants to publish and produce their content collaboratively and enable two-way interaction between its users, such as YouTube, Facebook, TikTok, Sina-microblog, Instagram, and WeChat.

2.1.2. Communication behaviors on social media

Given the rapid advance of mobile Internet in the world, social media has been considered the valuable communication tools in journalism, public relations, marketing, advertising, and public health (Lipschultz, 2017; Westgate & Holliday, 2016). Within the communication studies, several researchers have identified that exchanging and consuming digital information via multiple channels promotes a sense of belonging and then exerts a direct influence on all aspects of users' lives, such as health attitudes, consumption decisions and even mental health (Chou et al., 2018; Goh et al., 2013; Lin et al., 2016). Hence, from a practical perspective, a considerable amount of the literature has pointed out various social media communication strategies that can be deployed to improve brand loyalty, manage public crises, promote collaborative learning as well as establish trusted relationships between citizens and governments (Cheng, 2018; DePaula et al., 2018; Glucksman, 2017).

Drawing upon multiple distinctive characteristics of social media, communication scholars have endeavored to explore and increase its effectiveness by determining users' communication behaviors. To a large extent, several studies have found that sociality and information needs have become central motivations for Chinese social media users (Lien & Cao, 2014; Xie et al., 2017). Consequently, engagement and information behaviors on social media have become central issues for investigating users' communication behaviors and tracing public opinions and preferences. In general, one-way information usage patterns include passive information scanning and active information seeking, while information discussing is deemed as the two-way information usage pattern (Lovejoy & Saxton, 2012). In a similar vein, most past studies have focused on three types of information use patterns on social media, including information discussing, scanning, and information seeking (Jiang et al., 2021).

1) Engagement behaviors

In the literature, one of the most significant current discussions in social media communication is how to predict and promote users' active engagement by meeting their social needs (Shahbaznezhad et al., 2021). In the literature, the definitions of engagement behaviors vary in different disciplines. For instance, in the field of digital marketing, users' engagement behaviors have been summarized as a series of acts like co-creation or consumption of brand-related content via social media (Cvijikj & Michahelles, 2013; Hallock et al., 2019). Within communication scholars, recent studies have concerned public engagement in collaborative activities in virtual communities, including posting, liking, sharing, and commenting (Dolan et al., 2019; Ma et al., 2020). In this aspect, "liking" is considered a quick response that shows individuals' perception to some degree. In comparison, "sharing" is regarded as a medium level of engagement that indicates individuals' appreciation or preferences, and "commenting" necessitates more cognitive effort, which is considered the highest level of engagement (Isip-

Tan et al., Ngai et al., 2020). As it is becoming extremely difficult to ignore the vital impact of users' engagement behaviors on social media, a great deal of prior studies has revealed the association of characteristics of digital messages with a level of engagement, such as Bowles et al. (2020) and Shahbaznezhad et al. (2021). Thus far, several studies have convincingly shown that the content, tone, emotional appeal, and multimedia type of posts have impacted the amount of engagement on social media platforms, and that, in turn, affecting users' beliefs and behaviors in the real world.

2) Information scanning and information seeking

Recent investigators have begun to focus on users' information behaviors to trace and gratify their informational needs. In the literature, information behaviors refer to obtaining and processing information passively or intentionally. In the literature, information seeking and scanning have been considered two general strategies to acquire information among social media users (Shim et al., 2006; Waters et al., 2016). For the above reasons, much of the current literature pays particular attention to distinguishing between information scanning and information seeking, as well as proposing definitions of two terms.

Regarding information scanning, historically, this term has been used interchangeably to mean incidental exposure or casual information acquisition (Johnson, 1997; Tewksbury et al., 2001). Compared with information seeking, information scanning has been applied to situations where individuals encounter information less purposefully in the course of routine exposure to interpersonal sources or mass media (Niederdeppe et al., 2007; Hovick & Bigsby, 2016). In other words, it can be considered a spontaneous consequence of routine use of mass media that individuals obtain information in a purely non-strategic manner (Hornik et al., 2013). More importantly, what information scanning includes is any information yielding that can be reminded by individuals at a later time (Southwell et al., 2002). Furthermore, although scanning is unintentional information acquisition, scanners must pay attention to the information once mere exposure has occurred (Niederdeppe et al., 2007). To sum up, information scanning may be determined as exposure to information consisting of two components: unintentional information acquisition and recall. Regarding information seeking, prior studies primarily defined this term as looking for specific topics deliberately (Bright et al., 2005; Waters et al., 2016). In other words, information seekers are driven by their personal needs to bridge specific knowledge gaps (Lewis, 2017). What stands out in Table 2.1 is the differences between information scanning and information seeking.

Scholars have long debated the different impacts of information seeking and scanning in the literature. In this regard, for instance, several studies have pointed out that information scanners obtain a greater variety of knowledge than seekers during routine exposure to numerous information sources (Kelly et al., 2010; Zhu, 2017). Thus far, several studies have highlighted factors associated with public engagement in information scanning on social media, including digital literacy, demographic profiles, and multifactorial beliefs (Hornik et al., 2013; Ruppel, 2016). Conversely, several investigators have found that intentionally seeking specific information plays a larger role than scanning in influencing public behaviors because seekers are often more critical and active (Osawele et al., 2018; Tan & Goonawardene, 2017). Generally, all the evidence suggests that determining public communication behaviors is crucial to promoting disease prevention behaviors, influencing general lifestyle choices and consumption, as well as increasing the level of social knowledge.

Table 2.1. The comparison between information scanning and information seeking

Information scanning	Information seeking
scanners	seekers
passively/unintentionally	actively/intentionally
encounter/exposure to mass information	search/gather a specific topic
Information sources: mass media, interpersonal communication, social media, doctors	

(Source: Author created)

2.1.3. Individual differences in social media use: digital divide

With the increased penetration of information and communication technologies (ICTs) worldwide, considerable literature has grown around the theme of the primary digital divide, which refers to a separation between connected and disconnected people (Van Dijk, 2006). According to Gunkel (2003), the primary digital divide can be defined as disparities in access to ICTs caused by social and economic inequalities. It is generally agreed that the digital divide occurs on four levels: usage access, personal skills, motivation and attitudes, and types of usage (DiMaggio & Hargittai, 2001; Zillien & Hargittai, 2009). Although unequal access to the Internet has diminished every year, the primary digital divide doesn't disappear, especially in developing countries (Correa, 2016). In this context, scholars have turned their attention to the unequal access to socio-economic differences in differentiated usage of the ICTs, which has been called the secondary digital divide: the usage gap (Tsetsi & Rains, 2017; Van Deursen & Helsper, 2015). As such, despite users from different socio-economic statuses having similar degrees of ICTs access, they use these applications in unequal ways or for various purposes, which in turn have a potential impact on their personal development and future situations (Haight et al., 2014; Van Deursen & Van Dijk, 2014). For instance, it has been reported that people with higher socio-economic status (e.g., income, education) tend to engage in more skillful Internet activities (Correa, 2016).

The increasing reliance on social media platforms has recently led to a proliferation of studies focusing on social media usage divides. In fact, debates continue about whether social media provide potential opportunities for narrowing the digital divide. Several studies have demonstrated that the popularization of social media has facilitated the exchange and delivery of information, thus making it more accessible to everyone, especially to disadvantaged populations (Chen & Wang, 2021; Zhang et al., 2021). However, other studies have concluded that the usage divide has even been exacerbated due to the emergence of social networking platforms. Indeed, social media users have been less bounded by their socio-demographic status, while social media usage still has been driven by other inherent factors, such as personality traits (Zhang et al., 2021). For instance, in the social media era, findings have shown that social and individual determinants have an effect on social media use for information acquisition purposes, probably resulting in inequality of access to information (Haight et al., 2014; Koiranen et al., 2020). To sum up, the relevant studies regarding social media usage divides can be grouped into two aspects: a) individual differences in the choice of social media platforms and b) individual differences in the choice of information use patterns during the use of social media.

On the one hand, several investigations have shown significant differences in the choice of social media platforms during online information acquisition among population groups (Kim et al., 2014). In this regard, for instance, evidence suggests that females tend to spend more time on social media platforms rather than males, especially on those which have more interactive environments, such as Facebook and Instagram (Chukwuere & Chukwuere, 2017; Chen et al., 2015). Additionally, recent studies revealed that girls are more likely to engage in social media for both informational and interpersonal purposes (Muscanell, & Guadagno, 2012; Twenge & Martin, 2020). In the literature, age is another vital variable influencing social media use. It is worth noting that as avid Internet users and regular users of social networking sites, young adults are more likely to use Instagram, Snapchat, and TikTok, while Facebook or YouTube is used more broadly among those aged 65 and older (Auxier & Anderson, 2021; Hanan et al., 2018). In a similar vein, the research has confirmed that education and income also affect the usage of social media for consuming information and that higher income and higher education are associated with increasing social media presence (Hruska & Maresova, 2020; Kim et al., 2014).

On the other hand, as it has been noted that the primary purposes of accessing different social media platforms refer to informational purposes, there are a large number of published studies describing how social and individual determinants affect their information use patterns on social media. Recent observations have demonstrated that individual-level and socio-demographic predictors to motivate persons to search for information online are being younger, female, having higher education achievement, and having a higher monthly income (Bhandari et al., 2020; Jacob et al., 2017). These conclusions also accord with previous research above mentioned that those with higher socio-economic status are more likely to engage in more skillful online activities, not only for informational purposes but also for interpersonal purposes (Zhang et al., 2020). And individual differences in social media use for health information acquisition will be illustrated in more detail in a later section (see details on pp. 46-48).

2.2. Health communication

2.2.1. Definitions of health communication

Historically, given the multidisciplinary nature of health communication, its definition varies among researchers, and it is a concept difficult to define precisely. Although differences of opinion still exist in the literature, evidence confirms that health communication plays a crucial role in encouraging and influencing the decisions of individuals, policymakers, professionals, and authorities relevant to health issues (Schiavo, 2013). Remarkably, considering recent events about the coronavirus outbreak, it is becoming extremely difficult to ignore the central meaning of health communication that is conducive to reaching specific health goals for the community, individuals, and stakeholders (Ratzan et al., 2020).

Firstly, it is essential to clarify its history to elaborate on the definition of health communication. In prior decades, several scholars have summarized that the factors affecting the evolution of health communications refer to the growing emphasis on doctor-patient relationships, the advancement of the healthcare system, increasing problems regarding health disparities and discrimination, and more attention on disease prevention rather than treatment (Thomas, 2006). In other words, the emergence of health communication is the result of the advancement of communication skills and applied behavioral science, as well as increasing concern about public health in terms of HIV/AIDS prevention, smoking cessation, cancer prevention, and unwanted pregnancy all over the world (Kreps et al., 1998). Since the launching of the Stanford Heart Disease Prevention Program (SHDPP) in 1971, researchers have shown a growing interest in designing communication messages to increase the effectiveness of health campaigns (Rogers, 1994). In 1975, the International Communication Association (ICA) used the term “health communication” instead of therapeutic communication in response to the increasing need, that popularized this subject among scholars not only in the field of public health and healthcare but also in the field of mass communication and interpersonal communication (Freimuth, 2012).

In the last few decades, health communication analysis has become a multidisciplinary and multifaceted area that involves four levels of communication: a) intrapersonal health communication: it focuses on personal health self-management and mental processes, including health attitudes and beliefs (Kreps et al., 1998); b) interpersonal health communication: it puts emphasis on the relevant relationships influencing health outcomes, such as doctor-patient relationships and provider-consumer relationships (Parrott et al., 1992); c) group or organizational health communication: it explores the exchange of health information among members of families, health organizations, healthcare teams and authorities (Schiavo, 2013); and d) society health communication: it discusses the dissemination of health information via diverse mass media in order to influence knowledge, attitude, practice and ultimate health decisions of the targeted audience (Jackson, 1992). Generally, according to Schiavo (2013) and Rogers (1994), the defining features of health communication can be stated in terms of its delivering content, audience, and purposes.

1) Health-related information

In the literature, health-related information (HRI) has been considered persuasive messages disseminated via various channels with the aim of improving understanding, leading to greater consensus, and promoting relevant actions (Bernhardt, 2004; Krep et al., 1998). Since the nature of health communication is informational, educational, and fundamental, the delivering content encompasses all kinds of health-related information with a broad range of topics, such as knowledge, experiences, ideas, policies, and measures (Cho, 2011; Schiavo, 2013). According to previous studies, health-related information can be categorized into two main types: 1) expertise-based health information; and 2) personal experience-based health information (Eysenbach, 2007). And it primarily defined expertise-based health information as the specific content produced by such medical professionals to bridge the public knowledge gap and handle general uncertainty (Song et al., 2016; Metzger & Flanagin, 2011). In comparison, experience-based health information is defined as the messages generated by lay users to exchange personal stories and opinions with others having similar health concerns (Scola-Streckenbach, 2008).

Along with the advancement of the Internet, scholars have been interested in the existence of digital health information. It has been demonstrated that online health messages are closely associated with medication adherence and disease prevention (Kyriacou & Sherratt, 2019). Additionally, online health information also has been categorized into three types according to their social support provisions and requests: 1) emotional support: which refers to the communication of encouragement, understanding, empathy, and reassurance that can reduce emotion-related stress and make people believe that they belong to one community; 2) informational support: which provides suggestions, practical knowledge or effective ways on how to solve problems; 3) instrumental support: which provides physical assistance, such as financial support (Li, C., 2020; Shi & Chen, 2013).

2) Targeted audience

Regarding the audience in the health communication process, key groups and intended audience can be used interchangeably to indicate the target of health communication interventions. In this way, several studies head for the participatory nature of health communication, that all forms of health communication interventions have to understand the needs and preferences of a target audience, aiming to create feelings and promote engagement (Finset et al., 2020). In other words, receivers also are senders that forward health messages to a broader range of audiences (Shi et al., 2018). Hence, two-way communication has been considered more recommended during process of health education (Boonchutima & Pinyopornpanich, 2013). In this aspect, the intended audience of health communication includes vulnerable and underserved populations (Schiavo, 2013).

In prior studies, vulnerable populations tend to refer to high-risk groups for health problems, such as the elderly, pregnant women, children, migrant populations, and so on (Kreps, 2008). Meanwhile, the definition of underserved populations considers the specific groups who don't have adequate opportunities for health information or services due to their gender, race, social class, and other factors (Happe, 2017). In recent years, there have seen increasingly rapid advances in health communication that provides each person with more access to health infrastructure, services, and information. Therefore, previous studies have revealed that online health campaigns can contribute not only to improving individual health outcomes but also to promoting health equity all over the world (Ford et al., 2019; Kreslake et al., 2016). Recent consensus in public health communication has also indicated the importance of developing audience segmentation strategies by considering individuals' socio-demographic characteristics, national identity, and cultural features in more detail (Kreuter & McClure, 2004). In turn, defining the audience segment would be conducive to creating health communication programs customized to specific population subgroups, thereby promoting health behavioral changes

(Bol et al., 2020).

3) Purposes of health communication

In the literature, there appears to be some agreement that health communication's core purpose is improving public health and well-being (Thomas, 2016). Practically, for addressing the goals of the Healthy People 2030, weaponizing tailored health communication is crucial that can contribute to the proliferation of factual health-related information via multichannel, disseminating persuasive health messages for the key audiences and vulnerable groups, moving toward equitable health worldwide, as well as managing non-communicable diseases and chronic disease efficiently (Griffith, 2021). Hence, health communication is defined as a process of exchanging health-related information with the aim of influencing, empowering, and supporting individuals, patients, professionals, organizations, or policymakers, so that they will change or adopt health-related knowledge, practices, or policies, and eventually, this process will contribute to influence public health outcomes (Fortune et al., 2018; Schiavo, 2013).

2.2.2. Relevant concepts in the field of health communication

Among the studies around health communication, widely varying discussions about health outcomes, health attitudes, and behaviors have emerged.

1) Health outcomes

Health outcome is frequently used in existing studies to describe changes in knowledge, beliefs, attitudes, behavior, social norms, and policies. It can be classified into behavioral, social, and organizational outcomes (Bala, 2017; Coffman, 2002). In this aspect, Schiavo (2013) classified health outcomes into two types: a) short-term outcomes: which refer to process indicators pertaining to changes in knowledge and awareness; b) long-term outcomes: which refer to the final results related to behavioral, social, or organizational changes. Therefore, at the individual level, health outcomes can be assessed by measuring the improvement of health knowledge, relevant health attitudes, and health-related behaviors (Brusse et al., 2014). And at an organizational level, it focuses on advancing health communication technologies, government actions or country preparedness for public health emergencies, delivering health services and social services, and health system development (Chaudhry et al., 2020; Schiavo, 2013).

2) Health attitudes

In the literature, creating behavior changes in a large-scale audience has been considered as the primary health outcome (Armanasco et al., 2017). Evidence suggests that the first strategic imperative concerns raising public disease awareness about preventative measures (Ironmonger, 2015; Lawlor, 2018). Also, it has been conclusively shown that health attitude change is the primary motivator to predict health actions (Hardcastle et al., 2017; Sheeran et al., 2016). In existing studies, the term “health attitude” tends to refer to individuals’ confidence or agreement in general (Bates et al., 2020). And data from several sources have identified that increased knowledge is associated with favorable health attitudes (Ahmad, 2015; Roy et al., 2020). Altogether, increased health knowledge and attitudinal changes have been regarded as two essential preconditions for ultimate behavioral changes (Stonbraker, 2020).

3) Health behavioral changes

In recent years, as the prevalence of chronic non-communicable diseases has risen, the critical elements influencing health behavior decision-making have been illustrated in several studies based on health behavior change theories (HBCTs) (Fleary et al., 2018; Jeong & Bae, 2018). In particular, several health communication intervention designers seek to understand the underlying behavioral mechanisms to promote the uptake of preventative measures in the context of an ongoing outbreak of COVID-19, such as Blagov (2020). Consequently, there is evidence that one of the most significant indicators to evaluate health communication performance is whether and how an individual changes their behaviors (Boonchutima & Pinyopornpanich, 2013). In fact, researchers' greatest challenges in predicting public health behaviors are how to link motivators with final decisions and how to influence participants in long-term adherence. For the above reasons, specific models tied to health behavior changes have been widely built and examined, such as the Theory of Planned Behavior (TPB), Transtheoretical model (TTM), Social Cognitive Theory (SCT), Behavioral economics (BE), Self Determination Theory (SDT), Health Belief Model (HBM) and so on. In the last few decades, integrating social and behavioral sciences within health communication has been considered a critical development that can offer a comprehensive vision for monitoring and understanding population health (Hekler et al., 2020; Yastica et al., 2020). Among these health behavioral models, in accordance to previous studies, the Health Belief Model and the Theory of Planned Behavioral Model have been widely chosen for different research purposes to capture the complexities of an individual's decision motives (Zhao et al., 2023). Both health behavioral models were empirically proved to be powerful theoretical frameworks in the Chinese context for quantifying the impact of an individual's underlying attitudes and cognitions on health outcomes (Liu, Y. et al., 2021).

a) Health Belief Model (HBM)

By and large, the Health Belief Model has been frequently adopted as a value-based conceptual model which focuses both on short-term and long-term changes, involving the influence factors such as demographic variables, psychological characteristics, and other cues (Figure 2.1) (Langlie, 1977). Since it was proposed in 1966, the Health Belief model has become the main explanation for why people engage in health actions, revealing the differing health beliefs that impinge on the individual's decisions (Kirscht et al., 1966). Regarding psychological factors, the Health Belief Model illustrates that individuals' awareness will eventually translate into behavioral change if people regard themselves as susceptible to an illness or disease (perceived susceptibility); if people realize the seriousness of leaving the illness untreated (perceived severity); if people know the effectiveness of behavioral changes available to reduce the risk of diseases (perceived benefits); or if they perceive fewer obstacles to following a recommended health action (perceived barriers) (Rosenstock et al., 1994; Tovar et al., 2010). Cues to action can be internal or external, including media coverage, advice from interpersonal communication, illness of friends or family members, and other related factors in one's environment (Champion & Skinner, 2008; Jones et al.,2015). Additionally, self-efficacy also has been recognized as a critical motivator associated with ultimate actions that reflects an individual's perceptions or evaluations of their abilities (Rosenstock et al., 1988). In prior studies, quantitative methods grounded in Health Belief Model have been widely chosen to assess the predictors of general intent or behavior change regarding a specific health issue, such as COVID-19 vaccination, smoking cessation, and mental health (Nobiling & Maykrantz, 2017; Shin & Cho, 2017; Wong et al., 2021).

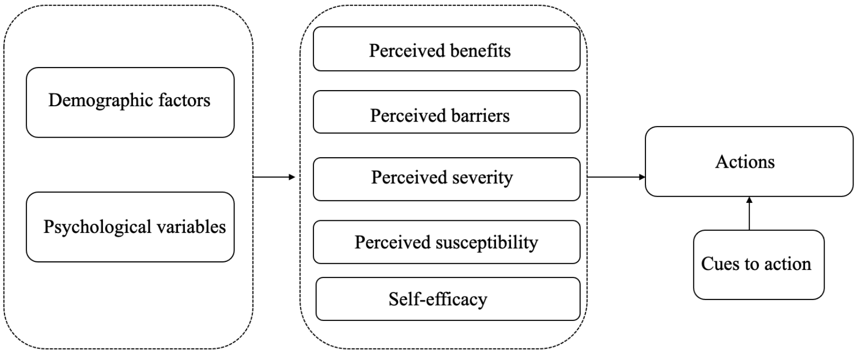


Figure 2.1. Health Belief Model

(Source: The health belief model and HIV risk behavior change (Rosenstock et al., 1994))

b) Theory of Planned Behavior model (TPB)

Since the Theory of Planned Behavior model (TPB model) was formulated by Ajzen (1991) as an extension of the Theory of Reasoned Action (TRA model), it has been widely applied to deal with the relationship between cognitions and behaviors in various domains, from psychological applied to public health, and from technology adoption to management (Bosnjak et al., 2020; Fishbein & Ajzen, 1977). As shown in Figure 2.2, the TPB model postulated that an individual's behavioral intentions could be determined by three psychological indicators: attitudes towards the behaviors, social norms, and perceived behavioral control, thereby strongly affecting actual human behaviors. In other words, an individual's intention has been recognized as the immediate antecedent of behavioral changes. Furthermore, each of these determinants can be defined as follows: behavioral attitude refers to the behavioral beliefs reflecting a person's subjective evaluation of the behavior's likely consequences, including both positive and negative perspectives; social norms refer to the degree to which important others approve or disapprove of engaging in such behaviors (known as subjective norms). Remarkably, social norms refer to perceived social pressure and others' expectations and relate to whether social referents themselves take action (known as descriptive norms) (Rivis & Sheeran, 2003). And perceived behavioral control is defined as the perceived ability or perceived power to perform a given behavior. These measurable control factors include required skills, money, social resources, and availability. That is, perceived behavioral control can be used to reflect whether an individual is capable or confident of the uptake of behaviors. Conceptually, it has been suggested that perceived behavioral control can be interchangeable with self-efficacy, which refers to a person's beliefs about whether they have the ability to overcome obstacles and how much the situation is under their control (Ajzen, 2020; Conner, 2020; Conner & Armitage, 1998).

In prior attempts to apply the TPB, a large number of empirical studies describe perceived behavioral control as a direct determinant of an individual's behavioral intention (e.g., Earle et al., 2019; Li, L., & Li, J., 2020). Specifically, the applications of the theory of planned behavior have proven to be reliable and efficient in explaining variables across health-related behavior categories over the past three decades (Godin & Kok, 1996; Hamilton et al., 2020). Also, the primary constructs proposed in TPB have been assessed to predict smokers' quit attempts in published studies, such as Norman et al. (1999) and Lareyre et al. (2021). Taken together, the TPB model offers a practical theoretical framework that can explain the complexity of human behaviors by measuring the direct impact of subjective norms and attitudes, as well as accessing the moderating effects of perceived behavioral control (Kan & Fabrigar, 2017; Sniehotta et al., 2014).

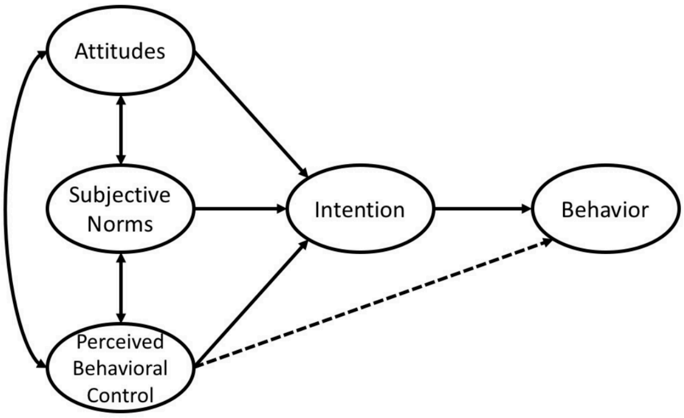


Figure 2.2. The Theory of Planned Behavior model

(Source: Attitudes, personality, and behavior (Ajzen, 2005))

2.3. Health information acquisition harnessing social media

Several recent studies have investigated how messaging content types and information acquisition patterns can lead to different health outcomes (Jiang et al., 2021). In line with the models postulated by Longo et al. (2001) and Long (2005), different information types and use patterns might affect people's health perceptions. According to Long (2005), active seeking and passive receipt are two common strategies that comprise the individual's information environment and engage users in the collective process of discovering knowledge simultaneously. Similarly, previous studies have pointed out that individuals can acquire health information not only through more purposefully seeking about a particular health concern but also through passively scanning information during the routine use of social media (Hovick & Bigsby, 2016). To be sure, it has been conclusively demonstrated that both information scanning and seeking can be vitally essential precursors of changing health beliefs, and behaviors, such as tobacco use, vaccine decisions, and vegetable consumption (Bigsby & Hovick, 2018; Moran et al., 2016).

To better understand the impact of health information exposure via social media, prior scholars classified information sources into two types, which are: a) informal or nonmedical sources: this category includes families, friends, and other non-professionals; b) formal or medical sources: this category includes professional medical sources, such as doctors, health organizations and authorities (Hornik et al., 2013). Due to its importance, evidence suggests that massive volumes of online health information are a double-edged sword.

In general, there is no doubt that the advancement of social media provides more accessible and available health information sources that are closely associated with an increased level of public health literacy, still, it also has created inequalities (Jacobs et al., 2017). As noted earlier, browsing and broadcasting are two common practices of social media users that can meet their needs. More recently, literature has emerged that offers contradictory findings about the relationship between online information acquisition and health outcomes, here, for instance, whether health-related social media use may result in increased health knowledge and favorable health beliefs (Strømme et al.,2018).

In some cases, it has been emphasized that exposure to multiple information sources through diverse channels positively influences on coping with stress and promoting subsequent decisions (Cawley, 2020; Schubbe et al., 2020). These conclusions seem consistent with the uncertainty reduction theory, which found that individuals tend to cope with negative emotions by obtaining additional information (Berger & Calabrese, 1974; Jiang et al., 2021). Along the same lines, recent studies have found that individuals who received more disease-specific knowledge via social media were more likely to hold stronger health attitudes and participate in health activities (Bowles et al., 2020).

Contrary to findings regarding the positive effect of information acquisition, recent works have established that contradictory or uncertain information is associated with public aversive emotions and even functional impairment (Fischhoff et al., 2018; Thompson et al., 2017). In particular, it has been noted that a wide variety of misinformation amplifying via social media exacerbates more distress and profoundly exerts a negative effect on the uptake of desired behaviors (Quinn et al., 2020; Warner et al., 2021).

2.3.1. Health information seeking behaviors

Health information seeking behaviors (HISB) are driven by seekers' knowledge insufficiency, personal preferences, and curiosity. In this way, a plethora of studies have focused on how online health information seeking impacted patient-doctor relationship, medical adherence, patient compliance, and individuals' health situation (Lalazaryan & Zare-Farashbandi, 2014; Tan & Goonawardene, 2017). In the digital age, online health information seeking is forecast to continually impact the level of knowledge and public health decisions by health web pages, social support groups, health applications, and social media platforms (Stellefson et al., 2018). Added to that, as individuals increasingly get involved in searching for health information via social media more than ever before, several studies have pointed out that these emerging behaviors have satisfied personal health-related needs, but the balance between medical professionals and non-specialists has been broken (Jia et al., 2021). Indeed, the potential benefits of online health information searching insofar as educating people and promoting self-management of chronic conditions (McMullan et al., 2019). Hence, online health information consumers have become more knowledgeable about treatment, symptoms, and diagnoses via spontaneous searches. They also have become more accountable for health-related issues, positively impacting their health (Lu et al., 2020; Maon et al., 2017). However, a process of gathering health information online has arisen due to an individual's uncertainty about a condition, alternatively, it could be a primary motivator for aggravating health anxiety as well (Basch et al., 2018). Consequently, people with a higher level of health distress tend to access online information more frequently for the purpose of seeking reassurance and relieving anxiety (Wang et al., 2021). On the one hand, these repeated searches with an excessive amount of time online have been recognized as cyberchondria which negatively influences public health outcomes (Starcevic et al., 2020). On the other hand, it has been observed that health information seeking via social media has become a preferred way to address stress-related issues (Ukonu et al., 2021).

2.3.2. Health information scanning behaviors

Regarding online health information scanning, there is a consensus that widespread health information acquisition via unintentional scanning has shifted how Internet users consider prevention behaviors and cope with their health-related issues (Glova & Escano, 2019). Among the general population, although information scanning is regarded as a passive exposure with little attention through social media use or interpersonal communication, this less active behavior is far more common than health information seeking that has been closely associated with positive health outcomes (Liu et al., 2020; Lewis et al., 2021). By extension, the literature suggests that the overburdening stream of information may lead to depressive symptoms, feeling of a loss of control, and misunderstanding of health conditions, known as information overload (Matthes et al., 2020). Following this definition, surveys such as that conducted by Honora et al. (2022) have found that the deluge of information accompanied by the COVID-19 pandemic has a negative effect both on preventive behaviors and vaccination intentions. In light of the digital age, given the limited capacity of information procession of social media users, several studies to date have highlighted the association between media exposure and anxiety during health crises (Liu, C., & Liu, Y., 2020).

2.3.3. The comparison of the impact of health information scanning and seeking

Overall, the wealth of online health information contributes to promoting users' participation in health decision-making by improving their health-related knowledge, as well as providing potential opportunities for the public to discuss and evaluate medical options (Liu & Jiang, 2021). Thus far, communication scholars have long debated the similar or differential impact of information scanning versus information seeking on specific health knowledge and public health choices.

On the one hand, previous studies have demonstrated that information scanning has influence far more than information seeking on public health attitudes and behaviors due to the richness of information, high frequency of exposure, and diverse information sources (Tan et al., 2012; Zhu, 2017). In this regard, according to Hornik et al. (2013), information scanning exerts a direct influence on personal health by increasing the probability of exposure to helpful information, presenting repeated reminders, and reinforcing descriptive or subjective norms. In short, prior studies have considered information scanning as one of the vital precursors of stronger health beliefs and more active engagement in relevant health behaviors (Hovick & Bigsby, 2015).

Conversely, several studies focusing on information seeking through social media have shown that individuals who search for specific-disease information intentionally will have higher self-care skills and more control over their health (Yamashita et al., 2018; Zhang, D et al., 2021). In other words, evidence support that a person who is much more motivated to search for health information, will be more likely to collaborate with health professionals to discuss their health issues, resulting in active health care involvement. However, systematic review research showed no evidence for the direct influence of health information seeking on health outcomes, heightening the need to investigate underlying mechanisms and determine any mediating variables (Jiang & Street, 2017).

2.3.4. Individual differences in social media use for health information acquisition: seeking versus scanning

According to the conceptual model of patient use of healthcare information for healthcare decisions (Long et al., 2001), the digital age created a complex information environment in which users can choose various types of health information following their needs and own situation, such as health status, socio-demographic factors, and information preferences. And then, many information sources, channels, and discussed topics may result in different health outcomes, depending on various personal and situational factors. Similarly, based on the expanded conceptual model of health information seeking behaviors (Long, 2005), the choice of health information acquisition patterns depends on a complex set of interactions among multiple personal and contextual factors, such as socio-economic status and insurance coverage, and these findings are also valid for information scanning acquisition (Alvarez-Galvez et al., 2020; Jiang et al., 2021) (see details in Figure 2.3).

Within the literature, demographic factors thought to be influencing health information acquisition, especially cancer information seeking behaviors (CISB), have been explored in several studies. Research has shown, for instance, that female is more likely to obtain health information through purposefully seeking than male, and the likelihood of health information seeking also increases with educational achievement (Adjei Boakye et al., 2018; Jung, 2014; Özkan et al., 2016). In past research, age and socio-economic status seem to affect the patterns of health information acquisition as well, and the younger generation and the participants with higher income were more likely to seek health information via the Internet (Jacob et al., 2017; Nelissen et al., 2015). Other contextual factors associated with health information acquisition include personal health conditions and health literacy. An individual with lower self-reported health status or health literacy tend to scan health information rather than seek information (Bhandari et al., 2020; Gedefaw et al., 2020). Based on the literature mentioned earlier, it has conclusively revealed that the critical preconditions of health information acquisition not only include age, education attainment, income, and gender but also include other inherent variables, in turn leading to disparities in health information acquisition and thereby increasing health disparities (Jacobs et al.,2017; Pálsdóttir, 2010; Räsänen et al., 2021).

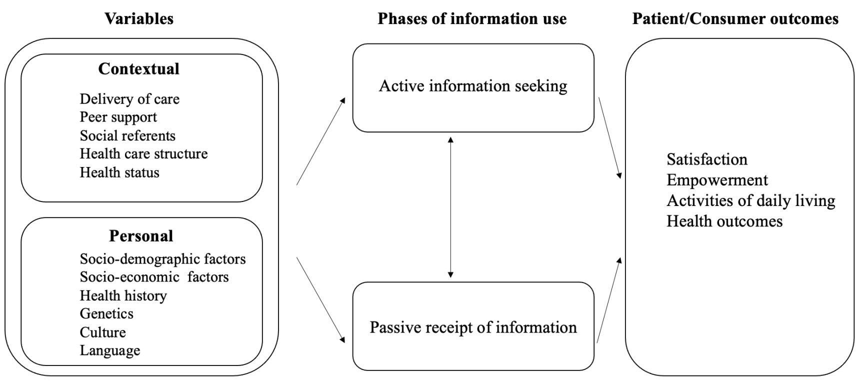


Figure 2.3. Expanded conceptual model of health information seeking behaviors and the use of information for health care decisions

(Source: Understanding health information, communication, and information seeking of patients and consumers: a comprehensive and integrated model (Long, 2005)).

2.3.5. Summary: the relationship between information behaviors and health behaviors

To conclude this section, previous studies focusing on the relationship between information behaviors and health behaviors can be grouped into two aspects. On the one hand, much of the current literature pays particular attention to evaluating the positive and negative impact of information behaviors on the health outcomes mentioned above. It has been conclusively shown that both health information seeking and scanning have prominent associations with an individual's increased knowledge level and substantial changes in health cognitions and behaviors. On the other hand, communication scholars elaborated a few conceptual models in order to explore the relationships between communication inequalities and health disparities, such as the Risk Information Seeking and Processing Model (RISP) (Griffin et al., 1999) and the Structural Influence Model of communication (SIM) (Viswanath et al., 2007). In this regard, although there have contrasting findings across studies, much of the literature still provides empirical evidence that inequalities in health information acquisition can ultimately produce disparities in public health (Hong et al.,2017; Vereen et al., 2021).

As shown in Figure 2.4, the structural influence model of communication (SIM) has pointed out that gaps in health information acquisition (such as exposure, access, and usage) based on individual, social and environmental determinants parallel health disparities in terms of knowledge, cognitions and prevention behaviors (Bigsby & Hovick, 2018; Viswanath et al., 2007). In other words, research demonstrates that the impact of communication behaviors on health outcomes was mediated by social determinants and social capital, including gender, age, income, educational attainment, and others (Colston et al., 2021). Or from another perspective, Figure 2.4 presents several structural antecedents, which propose that the relationship between social determinants and health outcomes may be mediated by the information environment and resources available, and this association also varies depending on different health cognitions (Bekalu & Eggermont, 2014). Theoretically, the SIM is an overarching framework that encompasses the inequalities among different subgroups and the relationship between health information exposure and health behaviors (Kontos et al., 2007; Konkor et al., 2019).

At this point, for instance, the literature has emphasized that the unequal access and use of information by socio-economic status contribute to the differences in smoking-related behaviors (Bekalu et al., 2022; Colston et al., 2022). Moreover, recent studies have shown that women, younger and people with higher socio-economic status reported a higher frequency of online health information use, thus resulting in a more holistic quality of life or better health outcomes (Bigsby & Hovick, 2018; Philbin et al., 2019).

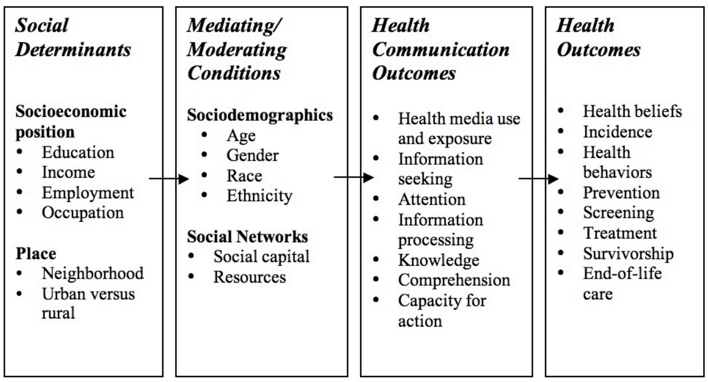


Figure 2.4. Structural Influence Model of communication

(Source : Mass media (Viswanath et al., 2007))

2.4. The impact of social media on smoking-related behaviors

For many years, public health campaigns via social media had more potential ability to increase health knowledge and influence public attitudes towards various health issues. Overall, recent evidence suggests that smoking education based on social media may lead to greater understandings and beliefs about the specific harms of tobacco use (Lazard et al., 2021). Moreover, harnessing social media is crucial to ensure a favorable atmosphere that is conducive to non-smokers keeping away from cigarettes or staying smoking free, especially for younger generations (Lloyd et al., 2018). In this way, the core objectives of anti-smoking social media campaigns are to develop tailored interventions and messages for smoking cessation, smoking reduction, and prevention education. And social media-based anti-smoking campaigns have been developed via online health communities, closed discussion groups, online self-help groups, anti-smoking-themed advertisements, or online health campaigns (Luo et al., 2021). In the literature, social media-based smoking cessation interventions have been defined as leveraging social media characteristics to provide informational and emotional support, such as specific knowledge, experiences, encouragement, and understanding (Meacham et al., 2021). Following these findings, a total of 138 published studies relevant to social media-based anti-smoking campaigns were recruited by searching on the Web of Science in May 2021. All included studies were published since 2015. Figure 2.5 provides the keywords clusters of studies mentioned above. In general, their focusing point falls under five headings:

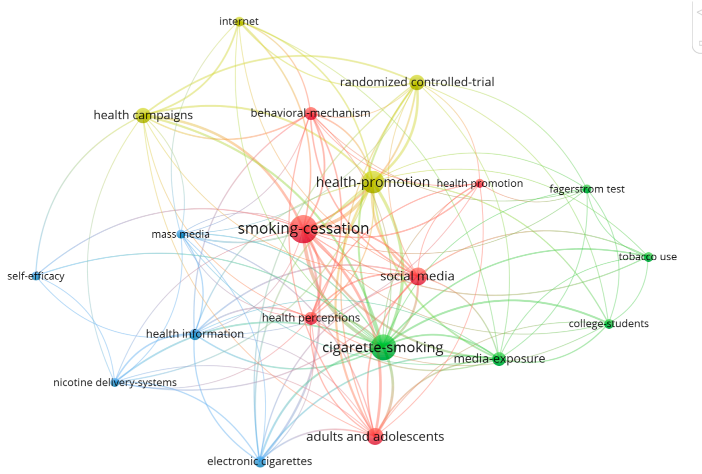


Figure 2.5. The keywords cluster of the literature (N=136)

(Source: author's creation through by Vos viewer)

2.4.1. Content-driven analyses

The researchers have focused on categorizing online discussions and coding digital tobacco-related posts to trace what users talk about on social media and illustrate the communication mechanisms of smoking-themed advertisements. On the one hand, existing studies employed content analysis to demonstrate the characteristics of persuasive messages relevant to anti-smoking. It has been conclusively shown that postings regarding perceived risk, social norms, and self-efficacy created greater audience engagement on social media platforms (Jiang & Beaudoin, 2016). Likewise, the literature has emphasized the critical roles of multimedia (text, pictures, and video) on smoking cessation behaviors by directly or indirectly influencing the awareness of the target audiences, such as their perceived behavioral control and subjective norms (Kulsolkookiet et al., 2018; Yu et al., 2015).

However, several studies have discussed the challenges and strategies for combating misleading or inaccurate information regarding anti-smoking via social media (Bae, 2018). On the other hand, much of the current literature pays particular attention to comparing anti-smoking and pro-smoking content. It has been concluded that pro-smoking messages reach users more efficiently and generate a greater number of reading than anti-smoking messages on social media (Park, 2019). As a result, the proliferation of pro-smoking messages across social media increased the smoking intentions of receivers (Yoo et al., 2016).

2.4.2. Analyses focusing on at-risk groups

Due to its potential ability to deliver social support at a low cost and reach large populations quickly, social media has created opportunities for health promotion agencies to target at-risk groups by increasing their level of knowledge and raising their cognitions about the health consequences of tobacco use (La Torre et al., 2020; Taylor et al., 2017). Several recent studies have carried out anti-smoking educational campaigns through social media for adolescents, pregnant smokers, and other vulnerable groups, such as Bird (2020) and Plant et al. (2017). Interestingly, evidence shows that women prefer relying on social media platforms for obtaining anti-smoking messages and are more aware of the harms of smoking compared to males (Jaafar et al., 2019). In this respect, the previous work has confirmed that the delivery of online anti-smoking information, and peer support emerging on social networking sites, reinforced favorable attitudes and decisions of pregnant smokers to quit smoking (Nguyen et al., 2012; Wu et al., 2017). An additional concern is the finding that younger users are more likely to be misled by thinking that smoking is fashionable, or smoking can relax them during the routine use of social media (Bae, 2018).

2.4.3. Comparison analysis

On the one hand, a great deal of previous research has compared the effectiveness of anti-smoking campaigns based on digital media with traditional media. On the other hand, much of the current literature made a comparison of anti-smoking campaigns harnessing different tools, including websites, e-health applications, and social media platforms. From this perspective, it has been conclusively shown that the advantages of social media use for smoking education include cost-effectiveness, interactive features, and more accessible information sources (Duke et al., 2014; Liao, 2019). Evidently, communication scholars have found that anti-smoking campaigns via social media have become influential for exchanging social support and providing personalized health content among smokers and non-smokers, especially among younger generations (Al Onezi et al., 2018). Regarding the interactive nature of social media, longitudinal data support a correlation between social interaction and the final decisions tied to anti-smoking. Much literature has revealed that digital media can enhance a smoker's cessation performance by making users have more network ties with others with the same health goals (Chung, 2016). Nevertheless, given its anonymous features, social media platforms provide an active and safe space for pro-smoking users to facilitate online relationship formation (Park, 2020).

2.4.4. Engagement level and adherence of users

The existing literature pays particular attention to which types of intervention generate higher engagement among participants. Overall, the evidence reviewed here clearly indicates that interactive content plays a key role in increasing the level of involvement (Pócs et al., 2021; Thrul et al., 2015). Furthermore, it has also been revealed that the frequency of reminders and daily auto messages are vital motivators for engagement in an anti-smoking campaign via social media (Pechmann et al., 2015; Ramo et al., 2015). In turn, increased sharing, commenting, or liking of anti-smoking content was significantly associated with subsequent changes in the receivers' smoking-relevant attitude (Pei et al., 2019). In parallel, the current studies have indicated that users are more likely to be persuaded by anti-smoking messages that are personally relevant or highly engaging (Sanders et al.,2018).

2.4.5. Effectiveness evaluation

In light of its potential effectiveness, the research to date has tested the efficacy of anti-smoking social media campaigns from four perspectives: a) analyze users' communication behaviors on social media, including engagement level (likes, shares, posts, follows, clicks and comments) and information processing (information seeking or scanning); b) measure individuals' changes in terms of knowledge, beliefs, attitudes and their information seeking action offline, such as their awareness on risks regarding tobacco use; c) evaluate receivers' antecedents of behavioral changes, such as quit attempts and contact with medical professionals; d) examine the ultimate health outcomes, which are regarded as a desired behavioral change of smokers and non-smokers, including sustained quit attempts, persuasion, and decline in smoking rates (Chan et al., 2020). Indeed, how to assess the smoking cessation outcomes after social media-based anti-smoking interventions has differed from study to study. Much of the studies reviewed here measured smoking cessation outcomes with intermediate quitting attempts, intention to quit smoking or persuasion, and relapse prevention (Namkoong et al., 2018). The remaining studies have been conducted based on 24-h Point Prevalence Abstinence (PPA), 7-day PPA, 30-day PPA, or 6-month PPA (Luo et al., 2020).

In line with the prior studies, different conceptual frameworks have been proposed to classify the predictors of anti-smoking behaviors, such as the health belief model, theory of reasoned action model, social norms theory, and the theory of planned behavior. On the one hand, it is now well established from a variety of studies focusing on underlying behavioral mechanisms of the target audience that knowledge-related outcomes can be considered as preconditioners, and greater beliefs are the mediators or motivators of the behavioral change outcomes (Laranjo, 2016; Naslund et al., 2017). On the other hand, there seems to be some evidence to support that beliefs regarding smoking consequences and subjective beliefs were affected by digital content, thereby influencing anti-smoking intentions (Al Agili & Salihu, 2020; Valencia-Arias et al., 2021). However, a much-debated question is whether there have any correlations between anti-smoking information acquisition and anti-smoking behaviors (Jaafar et al., 2019). Generally, some of the differences in health outcomes are caused by differences in quality, fear appeal, information sources, volume characteristics, affective tone, format, and content types of anti-smoking posts (Bigsby et al., 2017; Richardson et al., 2014; Samu & Bhatnagar, 2008). Similarly, the factors regarding public beliefs that drive behavioral changes vary significantly among different groups and social media platforms (Chung, 2019). Given all that has been mentioned so far, these studies provide reasonably consistent evidence for the efficacy of anti-smoking social media campaigns and demonstrate its shortcomings as well.

2.5. Brief summary

In conclusion, this chapter has attempted to summarize the literature on social media communication, health communication, and anti-smoking social media campaigns. Firstly, the studies reviewed here illustrated the homogeneity nature of social media and provided important insights into the communication behaviors of social media users, including information scanning, information seeking, and other engagement behaviors. Then, in the second section, five central themes emerge from the studies discussed so far: core objectives, information providers, content, target audience, and health communication outcomes. Conclusively, these studies support the notion that promoting public behavioral changes is critically important during the delivery of health campaigns. In the third section, a large and growing body of literature has investigated how health information acquisition impacts health outcomes. Taken together, the evidence presented in this section supports the hypothesis that there is a relationship between information behaviors and health behavioral changes, but this relationship has attracted conflicting interpretations. Conclusively, individuals who obtain sufficient health information from diverse sources are more responsible for their health management and decisions. Moreover, there seems to be some evidence to suggest that adverse effects have been caused by information overload, fake news, misleading information and more. Critically, a relatively small body of literature focuses particularly on the impact of scanned information acquisition. In the fourth section, such studies indicate the beneficial effects of anti-smoking health promotion via social media. Recently, public health efforts via social media have slowed the growth of smoking prevalence, providing a new avenue for addressing the tobacco epidemic worldwide. And information processing of social media users, in turn, leads to both short-term and long-term positive health outcomes regarding anti-smoking. In this aspect, different variables have been found to be related to anti-smoking behaviors, such as increased knowledge and greater beliefs.

To sum up, drawn from the existing literature, social media has served as a powerful communication tool to provide an interactive space for patients, health care professionals, and the general public where they can encounter, gather and share health-related content. Although such studies provided mixed evidence for the usefulness of anti-smoking social media campaigns, far too litter attention has been paid to the following themes:

a) A systematic understanding of the characteristics of anti-smoking-related posts disseminated via existing social media platforms in China is still lacking. In particular, there is much less information about the anti-smoking information environment on WeChat and TikTok. Similarly, there has been little discussion about the differences in content and format of anti-smoking information among different platforms.

b) In contrast to information seeking and engagement behaviors on social media, few published studies have been conducted to determine the possible effects of scanning information acquisition via social media on anti-smoking behaviors based on health behavior theories.

c) Despite the fact that the importance of prevention education among non-smokers has been recognized in prior studies, there is a notable paucity of empirical research that seek to identify the predictors of anti-smoking behaviors among non-smokers. In other words, the existing literature has not determined the impact of anti-smoking information acquisition in this group.

d) To date, a literature search revealing how social and individual determinants of social media users affect their anti-smoking information scanning in China is still not fully understood.

e) How the direct and indirect impact of anti-smoking information scanning via social media varies among different population subgroups remains unclear.

Consistent with the above argument, what remains unclear is what characteristics of anti-smoking content delivering across different social media platforms in China, how such information affects the anti-smoking behaviors of smokers and non-smokers, as well as whether or not scanning information acquisition via social media and its impact varies among different social groups.

For the above reasons, the current dissertation consists of three central studies to remedy these research questions. The first study set out to clarify and compare the characteristics of anti-smoking posts on different social platforms in China. Therefore, the second and third studies intend to determine the impact of anti-smoking information scanning via social media on the anti-smoking behaviors of social media users, who can be smokers or non-smokers. Here, the second study was designed based on the theory of planned behavior model that involved social norms, attitude, and perceived behavioral control as mediators. And the third study set out to explain the association of communication behaviors and health behaviors regarding anti-smoking based on the combination of the health belief model and structural influence model of communication. It was also designed intending to explore the influence of social and individual determinants on anti-smoking information scanning and identify the differences in pathways among subgroups. We hoped this dissertation would contribute to advancing our understanding of the target audience, content characteristics, and the effectiveness of anti-smoking posts disseminated through social media platforms in China.

CHAPTER 3

Study 1: Content analysis of anti-smoking-themed posts on social media platforms in China

3.1. Methods

3.1.1. Pilot study

A pilot study is a form of a feasibility study designed to evaluate the adequacy of the questionnaire or provide more knowledge to researchers that prevent the occurrence of too large-scale study (Lowe, 2019). Before data collection, a small pilot study was conducted during the April, 2021 to determine which social media platforms should be taken into account in content analysis and online surveys. Therefore, respondents' data were recruited by distributing a questionnaire via Credamo platform. Participants were asked to indicate the three top social media platforms frequently used in daily life and the most commonly used sources to obtain health information. Among 94 participants recruited, the most popular social media platforms refer to WeChat (85.1%), followed by Sina microblog (51.9%), TikTok (34%), and QQ (25.5%). In response to the second question, most participants (83%) reported that WeChat official accounts are considered the primary health information sources, followed by TikTok (49.8%) and Sina microblog (31.9%). Based on these results, the anti-smoking information will be collected from WeChat official accounts, TikTok, and the Sina microblog platform. Meanwhile, only these three social media will be mentioned in the current questionnaire.

3.1.2. Content analysis

Traditionally, in the communication field, one of the most well-established approaches for identifying specified characteristics of media messages is content analysis (Riffe et al., 2019). To a certain extent, content analysis is widely available for presenting the systematic and replicable analysis of digital posts in the internet era (Lacy et al., 2015). Overall, content analysis has been considered a set of research techniques that can be categorized into three types: synaptic analysis, lexical analysis, and thematic analysis (Oliveira et al., 2013). Operationally, it may involve qualitative and quantitative methodologies for analytically describing and examining textual or visual information (Schreier, 2012). Qualitative content analysis provides context-bound results by interpreting the underlying meanings of media messages, while quantitative content analysis offers context-free results by assigning numeric values and using statistical methods (Riffe et al., 2019; Vaismoradi et al., 2016). In some cases, it was revealed that most content analyses involved a quantitative approach would usefully improve the reliability of the results (Krippendorff, 2004; Manganello & Blake, 2010).

In prior studies concerning health communication, thematic content analysis permits researchers to infer people's preferences and assess the consequences of exposure to health messages (Harvey et al., 2019; Ngenye& Kreps, 2020). Furthermore, thematic analysis approaches can be suited to explore the narrative materials by breaking digital texts into small units, interpreting them, and then grouping them into different categories (Oliveira et al., 2013). Therefore, in line with the aim of this study, thematic content analysis was employed to manifest the content of anti-smoking-related posts on social media in China, including topics, the basis of content, and social support provisions. And the questions about the differences between WeChat, Sina microblog, and TikTok were to be addressed using quantitative approaches.

3.1.3. Data collection

Data retrieval from three social media platforms (WeChat, Sina microblog, and TikTok) occurred between April 1, 2021, and July 31, 2021. In most recent studies, the keywords search method has been popularly adopted to capture digital texts relevant to a specific health issue or health campaign, such as Chung (2016). Accordingly, taking careful account of determining keywords before collecting such digital messages is essential that needs to consider the main findings of prior studies and the actual situation in a particular context (Hamad et al., 2016). Then, the Python programming scripts were implemented to crawl posts filtered for keywords related to anti-smoking automatically and continuously. Regarding ethical issues, firstly, the data on WeChat official accounts, Sina microblog, and TikTok is freely accessible to the public (Shi & Chen, 2014). Furthermore, all usernames were removed, and we only use aggregated data to present results in this paper, intending to avoid personal identification.

As most relevant studies have failed to demonstrate the categorization of the thematic content of anti-smoking messages delivered via social media platforms in China, firstly, we manually detected a baseline of user discussions about anti-smoking by using the platforms' search functions to determine the search strings. This approach is in keeping with previous studies concerning the health-related posts on social media platforms that reliable data analysis depends on gathering sufficient and applicable digital content (Li, J et al., 2020; Vaismoradi et al., 2013). In the current study, multiple keywords searches were performed, including smoking [吸烟], smoking cessation [戒烟], smoking ban [禁烟], smoking free [无烟], tobacco control [控烟], smoker [烟民], e-cigarette [电子烟] and second-hand smoking [二手烟].

Using the Python web crawler (a powerful tool to programmatically fetch and process data from web pages that can be built by writing a script with computer language), messages posted by all accounts were recruited. The total number of 28,718 anti-smoking-related posts was collected from WeChat, Sina microblog, and TikTok platforms during the study time frame. Regarding article selection, we first reviewed all messages manually to exclude posts irrelevant to smoking by using a binary coding approach. Then, we filtered all posts related to pro-smoking. Finally, we applied the final inclusion criteria to ensure all posts remained are about anti-smoking based on several definitions of anti-smoking information illustrated in this dissertation (see details on pp.80) (Figure 3.1). After data cleaning, 11,586 anti-smoking posts met all criteria, including 2259 posts on WeChat, 7562 on the Sina microblog, and 1801 on TikTok.

Considering the purposes of this study, we collected and recorded the following information for each post: content types, media types (text, video, and image), communicator types, and the index number, which can reflect the popularity of each post (Xi et al., 2020). In this regard, communicators are identified by the authentication of accounts. Furthermore, to understand the level of involvement, we recorded comment frequency and the count of shares and likes of each post collected from Sina microblog and TikTok. Similarly, we recorded view frequency, comment frequency, and the count of likes of each post recruited from WeChat official accounts.

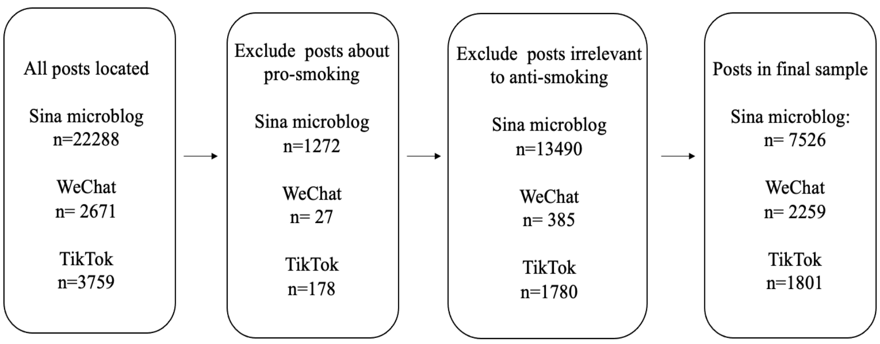


Figure 3.1. Post selection flowchart

(Source: author created)

3.1.4. Coding scheme

The coding procedure has been viewed as data reduction and theme development that permits researchers to explore the critical constructs presented in data (Vaismoradi et al., 2016). Table 3.1 below displays an overview of a coding scheme in which anti-smoking posts were categorized from four aspects: topic categories, content type, media type, and communicator type.

Table 3.1. Coding book

	Category	**Coding**
1	Topic category	1=tobacco use; 2=tips, tools, or effective ways of smoking cessation; 3= benefits of quitting smoking; 4= laws and regulations regarding smoking control; 5=city news and social activities about smoking control; 6=e-cigarette; 7= second-hand smoking; 8=others
2	Content type (basis of content)	1=only expertise-based information; 2=only experience-based information; 3=both; 4= neither
	Content type (social support)	1=informational support; 2=emotional support; 3=both; 4= neither
	Content type (pro-smoking or anti-smoking)	1=pro-smoking; 2= anti-smoking
3	Media type	1=only text; 2= with images or videos
4	Communicator	1=individual account; 2= governmental account; 3= health account; 4=media account; 5= others

To manifest the topic categories of anti-smoking-related posts, it was decided that the best methods to adopt for this study was inductive and deductive coding approaches because there were a few existing studies specifically dealing with the anti-smoking posts from TikTok and WeChat. And this method is advantageous in categorizing the themes of health-related posts published on social media platforms as well as identifying its characteristics (Li, J et al., 2020; Xi et al., 2020). After tagging and grouping parent classifications, the themes were organized into six categories, including tobacco use, smoking cessation, smoking control and the smoking ban, e-cigarette, second-hand smoke, and others, each of which is further grouped into following eight units (see details in Table 3.2):

a) the hazards of smoking, including statistics on mortality and adverse health consequences caused by tobacco use, such as lung disease.

b) tips, tools, or effective ways of smoking cessation: practical suggestions, guidance, medications, and steps to quit smoking.

c) benefits of smoking cessation: which include positive consequences of quitting smoking.

d) laws and regulations applied to tobacco control in China: such as smoking-free places.

e) city news and social activities, including voluntary activities, art exhibitions, and law education about smoking control.

f) e-cigarette: which include regulations restricting the use, sale, and advertising of E-cigarette and the hazards of e-cigarettes.

g) second-hand smoking: this introduce what second-hand smoke is and its health risk.

h) others: relates to the content

To better understand the content types of anti-smoking-related posts, we grouped them according to the basis of content (see Table 3.3): a) expertise-based information and b) experience-based information. Of the anti-smoking-related posts we recruited, expertise-based information refers to the content produced by governmental accounts, medical professionals, or health authorities that provide scientific data support or theoretical support, such as skills, health knowledge, and professional advice to maintain tobacco abstinence or control tobacco use, while experience-based content refers to laypersons' subjective experiences about anti-smoking, such as personal stories (Kosmidou et al., 2008; Song et al., 2016;).

Next, given several illustrations above mentioned that social media users are more likely to obtain and disseminate posts with social support provisions, the anti-smoking posts also were coded into two categories (see Table 3.4): a) emotional support provision: which refers to healthy behavior advocates or expression of concern and encouragement to anti-smoking, or dislike of smoking; and b) informational support provisions: which includes helpful guidance, knowledge, suggestions, advice, and explanations regarding anti-smoking (Park, 2019; Shi & Chen, 2014).

Additionally, a binary coding approach was employed to categorize anti-smoking posts based on pro-smoking or anti-smoking because previous studies have shown that the sharp growth in the amount of pro-smoking information emerging on social media has led to smoking initiation, especially in non-smoking young adults (Zhu, 2017). On social media, pro-smoking information has been not only generated and distributed by the tobacco industry but also by current smokers and young adolescents (Park, 2020) (see Table 3.5).

Regarding types of communicators, primary communicators of selected posts can be categorized into five types: a) individual accounts: which refer to personal accounts; b) governmental accounts: which are registered by governmental authorities or agencies; c) health accounts: which are created by public hospitals, health professionals and health organizations; d) media accounts: which are registered by traditional media, such as journals and TV station; and e) others: some accounts which published posts relevant to anti-smoking, such as universities and non-profit organizations.

Based on prior studies, the MAXQDA is one of the most common software for conducting content analysis. Its functions include information transcription, coding, statistical data analysis, and map building (Oliveira et al., 2013). Taken together, the present content analysis not only focuses on determining topic category, multimedia use, and communicators but also identifies the presence of social support provisions, pro-smoking posts, and expertise-based information in the content to be analyzed. Hence, all the coding work was carried out using MAXQDA Analytics Pro 2021, as it is particularly well suited to conduct thematic content analysis in social science research.

Table 3.2. Coding scheme--Topic classification and examples

Theme, Topic, Category		**Example (Chinse and English translation)**
1	**Tobacco use**	
1.1	The hazards of smoking	“烟草烟雾中含有超过 7000 种化合物，吸烟可导致胃癌，骨质疏松，和肺癌。 Tobacco smoke contains more than seven thousand compounds linked to lung cancer, osteoporosis, and stomach cancer.
2	**Smoking cessation**	
2.1	Tips, tools, or effective ways	“戒烟过程中，你可以通过跑步、嚼口香糖代替吸烟。”

		During smoking cessation, you can chew gum or run instead of smoke.
2.2	Benefits	“戒烟 1 年后后：体重增加，精神状况改善，肺癌的发病率降低。” After stopping smoking for one year, the smoker may gain some weight, their mental well-being will gradually increase, and the incidence of lung cancer will reduce.
3.	**Smoking control and Smoking ban**	
3.1	Laws and regulations	“《大连市控制吸烟条例》将于 2021 年 7 月 1 日起施行，以下公共场所禁止吸烟……” The Regulation on Smoking Control in Dalian shall go into effect on July 1st. Smoking will be banned in all public areas.
3.2	City news and social activities	“世界无烟日，志愿者们在公园开展活动，发放关于戒烟的宣传资料、还成功举行义诊活动。” On World No Tobacco Day, the volunteers host activities in the garden, hand out promotional materials about tobacco control and successfully hold the free clinic.
4.	**E-cigarette**	“尼古丁是电子烟的主要成分，WHO 指出电子烟不是戒烟的科学手段。” According to World Health Organization, electronic smoke can’t rise to quit smoking, and it also contains nicotine.
5.	**Second-hand smoking**	“二手烟危害极大，除了刺激眼鼻外，它还会直接危害他人健康。” Exposure to second-hand tobacco smoke has a profound negative influence that irritates the eye and hurts other health.
6.	**Others**	

Table 3.3. Coding scheme--Posts are categorized according to the basis of the content

Category		Example ((Chinse and English translation)
1	Expertise-based	"根据国家卫生健康委发布的报告显示，香烟中的尼古丁对肺功能有负面影响，同时促发慢性阻碍性肺病。" According to the report released by the National Health Commission of the People's Republic of China, nicotine adversely affects the functioning of the lung. It increases the risk of obstructive pulmonary disease.
2	Experience-based	"我今天去了朝阳医院的戒烟门诊，在医生的帮助下我计划明天开始戒烟，那里的医生态度很好。" I plan to quit smoking on the advice of the doctors of Chao Yang Hospital. They are friendly and help me a lot.

Table 3.4. Coding scheme—Posts are categorized according to types of social support

Category		Example ((Chinse and English translation)
1	Emotional support	" 我闻到旁边人的烟味了，太讨厌了！" " 让我们一起加油戒烟!" I can smell cigarette smoke. I hate it! Come on, let's cheer for smokers trying to quit.
2	Informational support	" 请注意，在以下地方吸烟，会被处以 50 元罚款" " 试试以下几个妙招，帮你轻松戒烟" Please note that there will be fines for people who smoke in these places…… Try these valuable tips for quitting smoking quickly.

Table 3.5. Coding scheme—Posts categorized according to pro-smoking or anti-smoking

	Category	Example ((Chinse and English translation)
1	Pro-smoking	"吸烟有助于我缓解压力，还是及时行乐吧！" Smoking can help me improve my mood. Let's enjoy it!
2	Anti-smoking	"吸烟有害健康，戒烟吧！" As we know, smoking is harmful to our health. Quit it!

3.1.5. Analytic strategies

Given the units of measurement can be determined based on convenience, hence, the unit for this study was a single anti-smoking-related post generated by a user. After collecting and coding, descriptive data were generated for all variables, including media types, communicator types, index numbers, topic categories, and content types. Then, a repeated-measures chi-square test was used to evaluate the differences in the proportions of media types, communicator types, and content types among the three social media platforms. Statistical analysis was performed using SPSS software (version 26). A P value < .05 was considered significant.

3.2. Results

3.2.1. Topic categories of anti-smoking-themed posts

Among 11,586 anti-smoking posts recruited, the topics can be grouped into eight categories: the hazards of smoking (n=4307), tips, tools, and effective ways (n=2045), city news and social activities (n=2226), laws and regulations (n=1598), benefits of smoking cessation (n=1554), second-hand smoking (n=1411), others (n=1447) and E-cigarette (n=1343). Furthermore, each selected anti-smoking post contains 1.38 topics mentioned above on average. The proportion of different topic categories of anti-smoking posts can be compared in Figure 3.2. It can be seen that the posts concerning the hazards of tobacco use dominated all three social media platforms (Sina microblog, n=2651; WeChat official accounts, n=757; TikTok, n=899). And the posts disseminated via the Sina microblog also were dedicated to city news and social activities regarding tobacco control (n=1591). In addition, the other dominant topics on WeChat platforms refer to effective ways of smoking abstinence (n= 811). Furthermore, E-cigarette (n=359) is the second most prominent topic on TikTok. Keyword clusters shown in Figure 3.3

that is quite revealing in several ways. First, except for smokers, the focus of anti-smoking posts is pregnant, adolescents and women. Of the 11,586 posts, lung cancer, carcinogens, and tumor are already being mentioned.

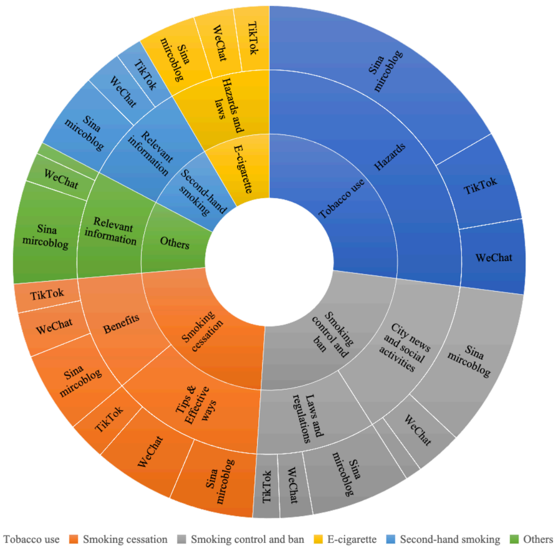


Figure 3.2. Theme and topic categories of anti-smoking posts (N=11586)

Figure 3.3. Keywords cluster of anti-smoking posts (N=11586)

3.2.2. Chi-Square Tests

1) Media type

As all anti-smoking posts delivered through TikTok are short videos, in this regard, we only compared the Sina microblog with WeChat official accounts. It can be seen from the data in Table 3.6 that the vast majority of the total anti-smoking messages on WeChat official accounts (n=2037, 90.2%) contain images and videos, as well as on Sina microblog (n=5648, 75%). Chi-square tests proved that multimedia had been used more frequently in WeChat official accounts than in Sina microblog, $\chi 2(1, N = 9785) = 235.84, p < .001, \phi = .155, p < .001$.

Table 3.6. Chi-square tests on the multimedia use between WeChat and Sina microblog

Variables	**WeChat n (%)**	**Sina microblog n (%)**	**Chi-square**	**df**	***P***
Multimedia	2037 (90.2%)	5648 (75%)	235.84	1	< .001
No Multimedia	222 (9.8%)	1878 (25%)			

2) Communicator type

Regarding the percentage of each type of communicator, 38.8% of the anti-smoking messages were posted by individuals (n=4592), followed by governmental accounts (n=2399, 20.7%) and health accounts (n=2050, 17.7%). The results of the Chi-square tests are displayed in Table 3.7. The results revealed that types of communicators were significantly related to different social media platforms $\chi 2(8, N = 11586) = 1919.40, p < .001, Cramer's\ V = .288\ p < .001$. Furthermore, it is apparent from Table 3.8 that most of the anti-smoking posts collected from the Sina microblog were disseminated by individuals and governmental accounts, while health accounts and media accounts were significantly more prevalent in WeChat official accounts and TikTok.

Table 3.7. Chi-square tests on the communicator types among three social media platforms

Variables	**WeChat (%)**	**Sina microblog (%)**	**TikTok (%)**	**Chi-square**	**df**	***P***
Individual	16.9%	47.4%	30.6%	1919.40	8	< .001
Governmental	15%	23.3%	16.9%			
Health	35.2%	13.1%	14.8%			
Media	20.3%	10.3%	31.5%			
Others	12.6%	5.8%	6.2%			

Table 3.8. Post hoc test-pairwise comparison among three social media platforms (communicator)

	Type of social media		
Type of communicator	WeChat	Sina microblog	TikTok
Individual	381	3570	551
	(-23.9)	(25.8)	(-7.8)
Governmental	339	1756	304
	(-7.5)	(9.5)	(-4.4)
Health	796	987	267
	(24.4)	(-17.6)	(-3.5)
Media	458	773	567
	(21.7)	(-15.8)	(23.2)
Others	285	440	112
	(-2.1)	(-14.9)	(-4.1)

3) Content type

As a preliminary step, Chi-square tests were employed to examine the difference among the three platforms regarding the percentages of anti-smoking and pro-smoking messages. As Table 3.9 illustrates, a significant difference was revealed ($\chi 2(2, N = 13163) = 331.38, p < .001, Cramer's\ V = .159\ \ p < .001$) and the pro-smoking messages are more common on Sina microblog platform.

Table 3.9. Chi-square tests the proportion of pro- and anti-smoking posts among three social media platforms

Variables	**WeChat n (%)**	**Sina microblog n (%)**	**TikTok n (%)**	**Chi-square**	**df**	***P***
Pro	27 (1.2%)	1272 (14.5%)	178 (9%)	331.38	2	< .001
Anti	2259 (98.8%)	7526 (85.5%)	1901 (91%)			

The data in Table 3.10 showed that types of social support provisions were significantly associated with different social media platforms $(\chi 2(6, N = 11586) = 271.02, p < .001, Cramer's\ V = .108\, p < .001$). A pairwise comparison pointed out that the Sina microblog provided more emotional support among three social media platforms than the other two. In contrast, both WeChat official accounts and the TikTok platform provided more informational support to smokers (see Table 3.11). As can be seen from the data in Table 3.10 and Table 3.12, over half of the anti-smoking posts disseminated on WeChat official accounts (50.1%) and TikTok (56.7%) are expertise-based information. Chi-square tests indicated that there is a significant difference among the three groups $(\chi 2(6, N = 11586) = 620.20, p < .001, Cramer's\ V = .164\, p < .001)$. In other words, experience-based information was more prevalent on the Sina microblog platform than on TikTok and WeChat. The more striking result from the data is that the posts based on expertise and evidence are significantly more common on WeChat than in the other two groups.

Table 3.10. Chi-square tests the content types of anti-smoking posts among three social media platforms

Variables	**WeChat (%)**	**Sina microblog (%)**	**TikTok (%)**	**Chi-square**	**df**	***P***
Social support provisions				271.02	6	< .001
Informational support	46.3%	34.1%	45.1%			
Emotional support	12.3%	18%	7.4%			
Both	32.8%	38.9%	42.4%			
Neither	8.7%	9%	5.1%			
Content type				620.20	6	< .001
Expertise-based	50.1%	39.5%	56.7%			
Expertise-based	10.2%	32.8%	25.4%			
Both	23.5%	16.3%	11.4%			
Neither	16.2%	11.5%	6.5%			

Table 3.11. Post hoc test-pairwise comparison among three social media platforms (social support)

	Type of social media		
Type of content	WeChat	Sina microblog	TikTok
Informational support	1045	2565	813
	(8.8)	(-12.3)	(6.6)
Emotional support	277	1351	134
	(-4.3)	(11.2)	(-10.0)
Both	740	2929	763
	(-6.0)	(2.0)	(3.9)
Neither	197	681	91
	(0.7)	(3.6)	(-5.5)

Table 3.12. Post hoc test-pairwise comparison among three social media platforms (basis of content)

	Type of social media		
Type of content	WeChat	Sina microblog	TikTok
Expertise-based	1131	2970	1022
	(6.2)	(-14)	(11.6)
Expertise-based	231	2465	457
	(-20.2)	(18.2)	(-1.9)
Both	530	1228	205
	(9.2)	(-2.4)	(-6.8)
Neither	367	863	117
	(7.6)	(-0.7)	(-7.4)

3.2.3. Engagement level

The results from the descriptive analysis of three index numbers are displayed in Table 3.13, including view frequency, comment frequency, and like frequency, which can reflect the extent of public engagement on three platforms. Meanwhile, the average frequency was calculated to compare the popularity of each platform. Overall, what stands out is the highest average number of comments, likes, and sharing on TikTok. Surprisingly, the anti-smoking posts derived from the Sina microblog attracted the least public involvement.

Table 3.13. Mean values of engagement of anti-smoking posts on each platform

	Comment (Mean)	**Like (Mean)**	**Share or Reading (Mean)**
WeChat	12,176	152,982	7455,899
	(5.38)	(67.72)	(3300.5)
Sina microblog	29,908	139,341	38,104
	(3.97)	(18.51)	(5.06)
TikTok	126,6358	29,002,669	5,789,058
	(703.14)	(16103.64)	(3214.4)

CHAPTER 4

Study 2: The impact of anti-smoking information scanning on anti-smoking behaviors of social media users in China: based on the TPB model

4.1. Theoretical framework and Hypotheses

4.1.1. The establishment of a theoretical framework

Throughout this study, the researcher conducted identification of the variables affecting the anti-smoking behaviors among smokers and non-smokers based on the extended theory of planned behavior model (Ajzen, 2005). As one of the health psychology approaches to understanding a wide range of health behaviors under different contexts and in diverse populations, the TPB stated that the predictors of an individual's intentions and behaviors include behavioral attitudes, subjective norms, and perceived behavioral control (Jiang et al., 2013; Baudouin et al., 2020). Therefore, as shown in Figure 4.1, the impact of anti-smoking information scanning on anti-smoking behaviors was hypothesized to be mediated by three belief-based components in the TPB model.

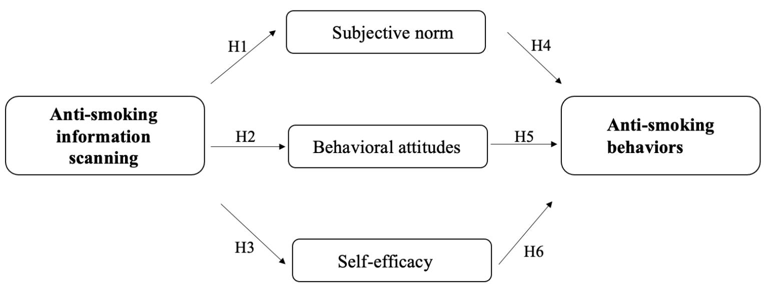


Figure 4.1. A theoretical framework based on the extended theory of planned behavior model

4.1.2. Interpretation of constructs

In line with previous studies, the dissemination of anti-smoking messages seeks to motivate the audience to engage in anti-smoking campaigns and increase public awareness based on its persuasive content characteristics, as well as diffusing knowledge based on one-way or two-way communication mechanisms (Jiang & Beaudoin, 2016). According to previous studies, anti-smoking information includes not only expertise-based information which is provided by medical professionals or health agencies, such as smoking norms, health advice or tips, and effects of tobacco use on health, but also includes experience-based information which is generated by the general public, including challenges or personal experiences, and pictures or stories regarding anti-smoking (Strekalova & Damiani, 2018). Relevant to the present study, anti-smoking information scanning involves attending to anti-smoking messages on social media that users are unintentionally looking for (Zhu, 2017).

Regarding three belief-based components in the TPB model, a behavioral attitude refers to personal evaluations regarding a given behavior involving positive or negative perceptions. Subjective norms refer to a person's own perceptions of whether their social referents think the person ought to engage in anti-smoking behaviors or whether significant others would express appreciation for it (Mercken et al., 2011; Tseng et al., 2019). More relevant to current literature, subjective norms relate to the degree of encouragement and appreciation that significant others give (Ajzen, 2020; Hagger et al., 2007). Hence, in this study, behavioral attitudes toward anti-smoking behaviors reflect an individual's perceptions about the likely outcomes of anti-smoking, such as health consequences and other quitting outcomes. Additionally, the perceived behavioral control was regarded as self-efficacy, reflecting an individual's evaluation of their ability and confidence in executing anti-smoking behaviors (Karimy et al., 2015; Zhao et al., 2019).

Research has consistently found that the target audience of social media-based health campaigns regarding tobacco control can be categorized into two types: current smokers (primary target audience) and non-smokers (secondary target audience) (Bennett et al., 2017; Luo et al., 2021). In prior studies, smoking behaviors have been recognized as daily tobacco use, including its number and mood state. From this perspective, current smokers are generally classified into two types: a) everyday smokers: who smoke cigarettes either daily or occasionally; b) someday smokers: who smoke occasionally, and the total number of cigarettes smoked reached more than 100 until the time of the survey (Vozoris & Stanbrook, 2011). Hence, for cigarette smokers, the main aim of anti-smoking campaigns is to promote smoking cessation and prevent relapse. Regarding smoking cessation behaviors, it encompasses ending a bad relationship with tobacco, greater abstinence, reducing relapse rate, and increasing quit attempts (Bala et al., 2017; Jacobs et al., 2016).

For non-smokers, including the families of smokers and the general public, the central objectives of anti-smoking campaigns refer to developing a better understanding of the risk related to tobacco use so that they can persuade smokers to stop smoking, prevent tobacco use in public places, protect themselves from exposure to secondhand smoke, and advocate for relevant public policies (Jiang & Beaudoin, 2016). In particular, smoking education via social media for non-smokers seeks to reduce initial intentions among youth to take up smoking (Chauhan & Sharma, 2017; Halkjelsvik & Rise, 2015). In other words, the anti-smoking behaviors of non-smokers focused on their persuasive intentions and greater beliefs, such as their willingness to encourage others to quit smoking or advocate the campaigns to their social referents and their increased awareness of how to protect themselves (Chan et al., 2020; Namkoong et al., 2018).

4.1.3. Research hypotheses

In the literature, researchers posit that the persons with higher self-reported exposure to health knowledge also hold favorable behavioral attitudes, which indeed promote health behaviors (Yanti et al., 2020). Specially to take actions to quit smoking, a general enhancement of knowledge regarding tobacco uses and skills regarding smoking cessation can be considered the most proximal predictor of positive behavioral attitudes (Liu& Tan, 2009; Zhao et al., 2019). Furthermore, the persons who grasp more useful information regarding tobacco use will be more likely to better understand the health consequences and importance of smoking control, which in turn stimulates smokers' quit attempts (Li et al., 2014; Khandeparkar et al., 2021).

In addition, existing research recognizes that the propagation of anti-smoking messages is an influential part of communicating positive social norms and providing social reasons for smoking cessation (Cohen et al., 2007). In other words, repeated exposure to anti-smoking messages can make non-smokers feel that others approve of them, whereas making smokers feel that others encourage them to quit smoking (Kim et al., 2018). As prior studies have found, self-efficacy is hypothesized to be a function of an individual’s increased knowledge (Cho et al., 2021). Therefore, the hypotheses were proposed as follows:

H1: Anti-smoking information scanning via social media exerts a positive influence on subjective norms;

H2: Anti-smoking information scanning via social media is positively associated with favorable behavioral attitudes towards anti-smoking;

H3: Anti-smoking information scanning via social media is directly correlated to increased self-efficacy.

In line with existing studies, favorable behavioral attitudes have been recognized as significant antecedents of adopting such anti-smoking behaviors (Alton et al., 2018; Namkoong et al., 2018). Out of the three main psychological factors in the TPB model, research has consistently heightened the prominent roles of social norms during the process leading to actual anti-smoking behaviors that an individual's perceptions of their social referents' evaluations of smoking influence intentions and behaviors (Dono et al., 2020; Lu et al., 2021). In accordance with this proposition, quitting intentions and cessation behaviors can be promoted in some circumstances where significant others disapprove of smoking (Schoenaker et al., 2018). According to Hosking et al. (2009) and Hassan et al. (2016), the findings demonstrate that favorable attitudes contribute to the greater effectiveness of influencing intentions than social norms in more individualistic cultures, whereas the effect of social norms is more significant as compared with behavioral attitudes in predominantly collectivistic cultures (Hassan et al., 2016

Considering the impact of self-efficacy, previous studies show that it positively predicted the increased likelihood of preventing tobacco use (Cousson-Gélie et al., 2018). More generally, an individual's perception of the degree of confidence in overcoming barriers is associated with a more or less likely adoption of a giving behavior (Zhao et al., 2019). Hence, the hypotheses were formulated as follows:

H4: Subjective norms have a positive influence on actual anti-smoking behaviors;

H5: Favorable behavioral attitudes towards tobacco use have a positive influence on anti-smoking behaviors;

H6: Self-efficacy is positively associated with anti-smoking behaviors.

4.2. Methods

4.2.1. Online questionnaire

In fact, the use of questionnaire data has a relatively long tradition within social science research. Meanwhile, a proliferation of studies focusing on online relationships and information consumers has led to a dramatic increase in the use of online surveys (Wright, 2005). Up to now, the questionnaire has become the most indispensable measurement tool for estimating communication behaviors and evaluating the impact of digital media, such as Farooq et al. (2020). In recent years, online surveys have been defined as mix-device surveys that can assure participant diversity and flexibility (Evans & Mathur, 2018; Toepoel, 2016). Regarding the design of the online survey, it has been conclusively shown that the response rate is highly influenced by ethical aspects, logical conversation, the layout of the questionnaire, and respondent interest (Saleh & Bista, 2017). Recent advances in mobile internet and computer-mediated communication in China have facilitated the distribution of questionnaires (Cui & Wu, 2019). Hence, it was decided that the best method to adopt for this investigation was to gather data by conducting an online survey.

4.2.2. Questionnaire distribution

A self-administrated questionnaire was employed to recruit the participants who meet the following conditions: a) aged 18 and above and b) use social media in daily life. This questionnaire was written in Chinese and consisted of four parts, including items on personal information (age, gender, monthly income, level of education, smoking status, and social media use habits), anti-smoking information scanning, three psychological constructs of the TPB model (attitudes, subjective norms, and self-efficacy) and self-reported anti-smoking behaviors. Above of all, a pre-test was conducted to determine the readability, accuracy and logical order of the questionnaire. After evaluating the questionnaire, it was distributed through Credamo, WeChat, Sina microblog, QQ, and Zhi Hu platforms from the beginning of September 2021 to the end of October 2021 in order to collect as much data as possible. According to the previous studies, recent advances in Credamo platform have facilitated respondents' data collection of various investigation for different purposes (He et al., 2021). On this professional online Chinese survey platform, questionnaire is randomly distributed across more than 30 administrative provinces in China (Wang et al., 2022). Additionally, many researchers have utilized WeChat, Sina microblog, QQ and Zhi Hu platforms to collect respondents' data with the snowball sampling technique, such as Liu, L et al (2018) and Yi et al (2021). It means that the present questionnaire will be distributed via a personal account to their contacts. Then, the first receivers will forward this questionnaire to their social referents, and so on. Furthermore, informed consent was given to ensure that the participants knew the objectives of this research and the confidentiality and anonymity of the questionnaire. Ethical approval was obtained from the ethical committee of the University Institute of Lisbon (95/2021) (Annexes A).

4.2.3. Measurement

Previous studies have summarized that there have three metrics of measurement of information scanning, including its activeness (the likelihood of coming across information), breadth (the total number of information sources), and depth (recall) (Niederdeppe et al., 2007). At baseline in prior studies, the frequency of exposure to anti-smoking information and diverse social media sources were measured (Bigsby & Hovick, 2018; Zhu, 2017). Hence, participants were asked how often they have been bombarded with various strategic or nonstrategic anti-smoking information during the routine use of social media. The response actions ranged from 1 (=never) to 5 (=several times each day) ((Romantan et al., 2008).

For gathering reliable information from participants, all the measures of three belief-based constructs were designed based on the standardized guidelines for TPB questionnaire development, including Ajzen (2002), Francis et al. (2004), and Oluka et al. (2014). Here, three items were included to measure the attitudes toward anti-smoking, according to Kaimry et al. (2005) and Mercken et al. (2011). Participants were asked to evaluate possible outcomes of anti-smoking behaviors, including better breathing and decreased prevalence of tobacco-related diseases. Responses for each term were scored using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Selection of two items to access subjective norms was carried out based on Dono et al. (2020) and Eisenberg & Forster (2003) that the participants were asked whether their parents, important friends, and lovers would encourage them to quit smoking or persuade others to stop smoking and whether their important social referents would show appreciation for their anti-smoking behaviors, the scores for each term ranged from 1 (very unlikely) to 5 (very likely).

Four items measuring the self-efficacy of the participants were derived from prior studies by Zhao et al. (2019) and Reisi et al. (2014), involving three aspects as follows: a) confidence in protecting myself by expressing refusal to smoke in public spaces passively; b) capable of supporting tobacco control and c) suppress smoking cravings under specific emotional situations. Responses were scored based on a 5-point Likert scale.

In the present research, a single question was set out, focusing on the actual anti-smoking behaviors of smokers and non-smokers: “Have you ever attempted to stop smoking or persuade others to quit smoking?” Answers were rated on a 5-point Likert differential scale, ranging from 1 (never) to 5 (several times) (Abroms et al., 2015; Yu et al., 2015).

4.2.4. Data analysis

Based on prior findings, partial least squares structural equation modeling (PLS-SEM) was adopted to determine relationships between latent variables that refer to anti-smoking information scanning, three psychological factors, and anti-smoking behaviors. Furthermore, the reasons for choosing this method in the current study are as follows: a) the reviews of PLS-SEM applications in the social science discipline ensure that PLS-SEM is applicable for unrestrictedly estimating relationships of reflective and formative outer models based on a series of ordinary least square (OLS) regressions (Chin, 1998); b) In light of several advantages extensively discussed in prior studies on PLS-SEM, most researchers mentioned that PLS-SEM is suitable for explaining both focused model (a small number of endogenous latent variables measured by a relatively large number of exogenous latent variables) and unfocused model (the number of endogenous latent variables is higher than the number of exogenous latent variables) (Hair et al., 2012); c) Considering data characteristics, on the one hand, PLS-SEM has been utilized to work with normal and non-normal data given its distribution-free character (Henseler et al., 2009). On the other hand, this method offers an effective way of handling with ratio scaled variables (Jakobowicz & Derquenne, 2007); d) Considering sample size issues, although existing studies confirmed that PLS-SEM works well large and small sample sizes, Barclay et al. (1995) concluded that the minimum sample size should be ten times the number of paths in the proposed model and e) Notably, practical advantage of using PLS-SEM is that it is not restricted by the utilization of single-item measurement in a questionnaire (Fuchs & Diamantopoulos, 2009; Hair et al., 2012). Taken together, the outer model of this study was composed solely of reflective indicators. Regarding data characteristics, it meets the minimum sample size requirements (n=60), and a 5- point Likert scale was used to measure all constructs that ensure normal distributions and continuous data. Regarding measurement, five constructs in this model were accessed by at least one item, so PLS-SEM was chosen.

To identify the reliability (indicator reliability and internal consistency reliability) and validity (convergent validity and discriminant validity) of this reflective model, outer loadings, composite reliability (CR), average variance extracted (AVE), Fornell-Larcker criterion, and Heterotrait-Monotrait criterion (HTMT) were assessed firstly by running PLS-SEM in Smart PLS 3.3. Then, complete bootstrapping with 5000 resampling procedures was run.

After significance testing, multigroup analysis (MGA) was employed as this approach is applicable for facilitating the explanation of moderating effects, in a similar vein, determining the significant differences across predefined data groups (Chean et al., 2020). Hence, the participants were divided into two subgroups that also ensured similar sample sizes for each group, one includes smokers, and the other contains non-smokers. After group generation, the measurement invariance of composite models (MICOM) procedure was performed to assess measurement invariance before making group comparisons (Henseler et al., 2016).

4.3. Results

4.3.1. Descriptive statistics

Table 4.1 presents the social demographic distribution of 806 participants that 56.9% were smokers (n=459) and 43.1% were non-smokers (n=347). The statistics show that 56.1% of the participants were female (n= 452), 99.4% had at least a high school education (n=801), and 82.9% earned more than 4501 yuan (US $706) per month. Of the 459 smokers, 60.6% of the participants were male (n= 278), and most of them were aged 26 years and above (n=386, 84.1%). It also shows that the proportion of smokers with at least high school education was 99.7% (n=458), and only 10.9% of the smokers earned less than 4501 yuan per month (n=50). Of the 347 non-smokers, the proportion of female (n=271, 78.1%) was higher than male (n=76, 21.9%). Similarly, a majority of the non-smokers ranged in age from 26 to more than 45 (n=238, 68.6%). Also, a majority of the non-smokers have at least a high school education (n= 343, 98.8%) and earn at least 4501 yuan per month (n= 260, 74.9%).

Table 4.1. Sample characteristics of the participants (N=806)

Factors	**Total (N=806)**	**Smoker (N=459)**	**Non-smoker (N=347)**
Gender			
Female	452 (56.1%)	181 (39.4%)	271 (78.1%)
Male	354 (43.9%)	278 (60.6%)	76 (21.9%)
Age [a]			
18-25	182 (22.6%)	73 (15.9%)	109 (31.4%)
26-34	454 (56.3%)	272 (59.3%)	182 (52.4%)
35-44	134 (16.6%)	88 (19.2%)	46 (13.3%)
More than 45	36 (4.5%)	26 (5.7%)	10 (2.9%)
Education			
Less than middle school	5 (0.6%)	1 (0.3%)	4 (1.2%)
High school graduate	115 (14.3%)	81 (17.6%)	34 (9.8%)
College degree or above	686 (85.1%)	377 (82.1%)	309 (89.0%)

Income			
Less than 4500 yuan	137 (17.0%)	50 (10.9%)	87 (25.1%)
4501-8000 yuan	288 (35.7%)	165 (35.9%)	123 (35.4%)
More than 8001 yuan	381 (47.2%)	244 (53.2%)	137 (39.5%)

[a] Mean (±SD) $_{(smokers)}$ =31.52 (±6.69); Mean (±SD) $_{(non\text{-}smokers)}$ = 28.89 (±6.44)

4.3.2. Hypotheses testing

1) Measurement model results

To evaluate the validity and reliability of measurement items within constructs, factor loadings, the composite reliability (CR), and the average variance extracted (AVE) of each item were computed (Ringle et al., 2015). In line with previous studies, item loadings and the composite reliability were set at a minimum of 0.7, thereby reflecting the acceptable reliability (Wong, 2016). Also, the accepted threshold value of AVE is equal to or greater than 0.5 to ascertain the convergent validity (Sarstedt & Cheah, 2019). Additionally, the variance inflation factors (VIF) lower than 5 have been used to judge the acceptable multicollinearity of the constructs (Hair et al., 2014). Finally, discriminant validity was assessed with the Fornell-Larcker criterion and the Heterotrait-Monotrait criterion (HTMT) as well (Sarstedt et al., 2017). Here, in this regard, the HTMT scores should be higher than 0.85 (Ringe et al., 2020).

Table 4.2 presents the remaining items whose outer loadings and composite reliability were higher than the minimum criterion after deleting one item measuring subjective norm. In addition, the value of the AVE square root for all the constructs ranged from 0.556 to 1.000, which satisfied the recommended threshold values. And the value of VIF for all the constructs was lower than the threshold of 5, suggesting no multicollinearity issue remained. The table 4.3

and 4.4 show the standard of discriminant validity based on the Fornell-Larcker and Heterotrait-Monotrait criteria, respectively. Based on all these assessments, there is strong empirical support that acceptable reliability and adequate validity were ascertained.

Table 4.2. The assessment of reliability and validity of the proposed model based on TPB

Construct, measurement item		Loading	VIF
Anti-smoking information scanning (CR:0.865; AVE:0.617)			
IN01	How often have you encountered information about anti-smoking on social media platforms?	0.827	1.768
IN02	How often do you ever read about posts that focus on anti-smoking information from diverse social media platforms, even if you don't subscribe to them?	0.804	1.761
IN03	Have you ever been exposed to such health segments regarding anti-smoking on social media when you were not trying to find out?	0.747	1.417
IN04	Can you remember any anti-smoking information obtained unintentionally during the routine use of social media?	0.759	1.520
Subjective norm (CR:1.000; AVE:1.000)			
SN01	Whether your parents, important friends, or lovers would encourage you to quit smoking or persuade others to stop smoking?	1.000	1.000
SN02	Whether your parents, friends, or lovers would show appreciation for your anti-smoking behaviors?	-	-
Behavioral attitudes (CR:0.790; AVE:0.556)			
BA01	Tobacco control will lower the chances of developing lung cancer	0.794	1.241
BA02	The prevalence of heart diseases will be decreased by engaging in tobacco control	0.716	1.204
BA03	Smoking-free environments are beneficial for good breath	0.725	1.176
Self-efficacy (CR:0.862; AVE:0.609)			
SE01	I can express dislike for passive smoking in public spaces	0.750	1.410

SE02	You feel agitated or tense. Are you confident that you will not smoke?	0.751	1.471
SE03	Are you confident you will persuade your families, friends, or lovers to quit smoking?	0.791	1.725
SE04	Are you confident that you can follow the smoking ban?	0.828	1.764
Anti-smoking behaviors (CR:1.000; AVE:1.000)			
B01	Have you ever attempted to stop smoking or persuaded others to quit smoking?	1.000	1.000

Table 4.3. Discriminant validity based on the Fornell-Larcker criterion

	B	**IN**	**BA**	**SN**	**SE**
Behavior[a]	1.000	-	-	-	-
IN[b]	0.375	0.785	-	-	-
BA[c]	0.384	0.232	0.746	-	-
SN[d]	0.310	0.235	0.379	1.000	-
SE[e]	0.497	0.439	0.311	0.353	0.781

[a] Behavior: anti-smoking behaviors

[b] IN: anti-smoking information scanning

[c] BA: behavioral attitudes towards anti-smoking

[d] SN: subjective norm

[e] SE: self-efficacy

Table 4.4. Discriminant validity using the Heterotrait-Monotrait criterion

	B	**IN**	**BA**	**SN**	**SE**
Behavior[a]	-	-	-	-	-
IN[b]	0.419	-	-	-	-
BA[c]	0.492	0.334	-	-	-
SN[d]	0.310	0.263	0.484	-	-
SE[e]	0.556	0.555	0.446	0.395	-

[a] Behavior: anti-smoking behaviors

[b] IN: anti-smoking information scanning

[c] BA: behavioral attitudes towards anti-smoking

[d] SN: subjective norm

[e] SE: self-efficacy

2) Structural model results

Results of the structural model analysis revealed that the constructs of the proposed model could explain 31.0% of the variance in anti-smoking behaviors. Furthermore, anti-smoking information scanning explained 5.5% of subjective norms, 5.4% of behavioral attitudes towards anti-smoking, and 19.3% of self-efficacy.

Figure 4.2 and Table 4.5 show that all the proposed hypotheses were supported. Anti-smoking information scanning significantly affects social media users' anti-smoking behaviors ($\beta = 0.247, p < .001$) by shaping their subjective norm ($\beta = 0.235, p < .001$), behavioral attitudes ($\beta = 0.232, p < .001$) and self-efficacy ($\beta = 0.439, p < .001$). As postulated, evidence suggested that subjective norm ($\beta = 0.083, p < .05$), behavioral attitudes ($\beta = 0.229, p < .001$), and self-efficacy ($\beta = 0.396, p < .001$) had a statistically positive association with anti-smoking behaviors.

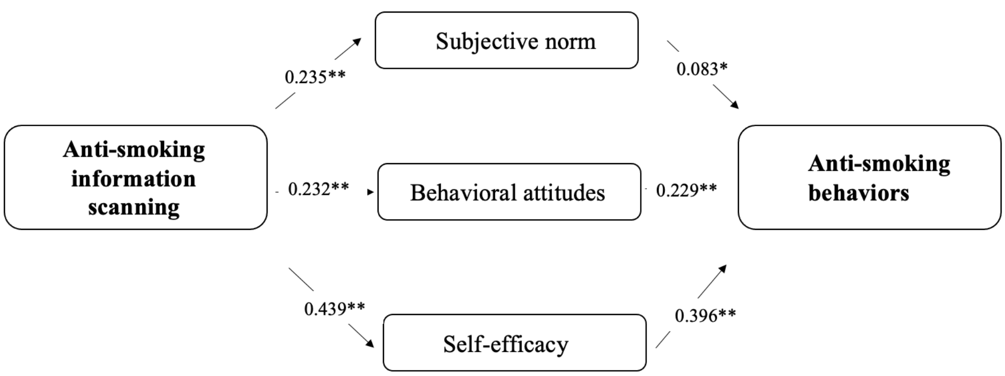


Figure 4.2. Path coefficients of the proposed relationships

Note: significance level: *P< .05, **P< .01

Table 4.5. Results of hypotheses testing, path coefficients, t-statistics, f^2 value, and p-values

Hypothesis	Relationship	$\boldsymbol{\beta}$	T-value	*P*	f^2
H1	IN and SN	0.235	6.052	.000	0.058
H2	IN and BA	0.232	5.989	.000	0.057
H3	IN and SE	0.439	13.459	.000	0.239
H4	SN and B	0.083	2.361	.018	0.008
H5	BA and B	0.229	6.466	.000	0.062
H6	SE and B	0.396	11.192	.000	0.191

3) Results of multigroup analysis between smokers and non-smokers

Table 4.6 presents the differences in the mean values of five constructs in the proposed model between smokers and non-smokers. Results of the independent t-test demonstrated that the smokers reported significantly higher mean values of anti-smoking information scanning than non-smokers, t (593.1) = 4.801, $p < .001$, while the level of behavioral attitudes was higher among non-smokers, t (804) = 2.679, $p < .01$. And none of the remaining differences was significant.

The partial measurement invariance was established by performing the measurement invariance of composite models (MICOM) procedure. Accordingly, the proposed model explained 43.1% of anti-smoking behavior among smokers, whereas, for non-smokers, it was 18.2%. In addition, the R^2 for subjective norm, behavioral attitudes, and self-efficacy in the smokers was 0.127, 0.093, and 0.165, whereas, for the other group, it was 0.026, 0.042, and 0.276, respectively. The results of the multigroup analysis, as shown in Table 4.7, indicate significant differences in only two paths. First, there was a significant positive correlation between anti-smoking information scanning and behavioral attitudes among smokers ($\beta =$

$0.356, p < .001$) and non-smokers ($\beta = 0.162, p < .001$), and a significant difference in this relationship was observed (Diff=0.194, $p < .05$). Second, no statistically significant correlation was found between behavioral attitudes and anti-smoking behaviors among non-smokers. In contrast, behavioral attitudes affect the anti-smoking behaviors of smokers significantly ($\beta = 0.315, p < .001$) (Diff $= 0.207$, $p < .01$). There was no observed difference in the remaining path coefficients.

Table 4.6. The difference in mean values of the constructs between smokers and non-smokers

Variables	Smoker	Non-smoker	T-value	*P*
Information scanning	4.13 (±0.58)	3.88 (±0.83)	4.801	.000
Subjective norm	4.25 (±0.73)	4.33 (±0.69)	1.443	.149
Behavioral attitudes	4.39 (±0.51)	4.48 (±0.43)	2.679	.008
Self-efficacy	3.74 (±0.84)	3.74 (±0.74)	0.142	.887
Anti-smoking behavior	4.08 (±0.85)	4.12 (±0.85)	0.598	.550

Table 4.7. Results of multigroup analysis between smokers and non-smokers

Hypothesis	Smoker	Non-smoker	Diff.	*P*
H1	0.305**	0.204**	0.101	.181
H2	0.356**	0.162**	0.194	.011
H3	0.407**	0.526**	-0.119	.051
H4	0.122**	0.035	0.086	.236
H5	0.315**	0.109	0.207	.004
H6	0.395**	0.378**	0.017	.804

Note: significance level: *P< .05, **P< .01

4.3.3. Post-hoc data analysis: Demographic effects

As noted above, previous research comparing different population groups has found that social and individual determinants are significantly related to online health information acquisition, mediating the effect of digital health messages on health outcomes (see details in Chapter 2.3.4). From this perspective, the post-hoc analyses were conducted to explore whether the socio-demographic factors and smoking status of all the participants exert influence on their anti-smoking information scanning via social media, including One-way ANOVA tests, Pearson's correlation analysis, and multiple linear regression analysis. Similarly, the demographic effects on anti-smoking information scanning among the smokers and non-smokers were examined respectively by performing these statistical strategies mentioned above. In addition, multigroup analysis (MGA) was used again to quantitatively analyze the differences in the total effect of anti-smoking information scanning on the participant's anti-smoking behaviors. To ascertain a similar sample size for each group and to facilitate the analyses, all the participants were divided into two or three subgroups according to their age, gender, income, education level, and smoking status.

1) Demographic effects on anti-smoking information scanning among all the participants

a) Comparison analysis

As shown in Table 4.8, One-way ANOVA tests revealed that there were significant differences in anti-smoking information scanning via social media platforms in gender groups (t (799.8) = 2.528, $p < .01$), age groups (F (2, 803) =52.631, $p < .001$), and monthly income groups as well (F (2, 803) =45.517, $p < .001$). Also, participants who are current smokers reported significantly higher value of anti-smoking information scanning via social media (t (593.1) = 4.801, $p < .001$). However, no significant difference between the two educational groups was evident.

Table 4.8. One-way ANOVA tests on anti-smoking information scanning among all the participants (N=806)

	Anti-smoking information scanning (Mean/± SD)	F value	*P*
Gender			
Female	3.97 (±0.76)	2.528	.012
Male	4.09 (±0.64)		
Age			
18-25	3.57 (±0.83)	52.631	.000
26-34	4.16 (±0.61)		
More than 35	4.14 (±0.62)		
Education			
High school graduate and below	4.10 (±0.70)	1.233	.218
College degree or above	4.01 (±0.71)		
Income			
Less than 4500 yuan	3.54 (±0.82)	45.517	.000
4501-8000 yuan	4.05 (±0.68)		
More than 8001 yuan	4.17 (±0.61)		
Smoking status			
Smoker	4.13 (±0.58)	4.801	.000
Non-smoker	3.88 (±0.83)		

b) Correlation analysis

According to the results obtained from Pearson's correlation analysis, the participants' smoking status, age, gender, and monthly income were found to be closely correlated to anti-smoking information scanning behaviors, $\gamma(806) = -0.175$, p < .001, $\gamma(806) = 0.270$, p < .001, $\gamma(806) = -0.087$, p < .05, $\gamma(806) = 0.291$, p < .001, respectively (see details in Table 4.9).

Table 4.9. Pearson's correlation analysis of participants' anti-smoking information scanning and five independent variables (smoking status, income, education, age, and gender)

	Smoking status	**Information scanning**	**Gender**	**Education**	**Age**	**Income**
Smoking status						
Information scanning	-.175**					
Gender	.386**	-.087*				
Education	.096**	-.043	.072*			
Age	-.181**	.270**	-.137*	-.147**		
Income	-.186**	.291**	-.188**	.189**	.424**	

Note: significance level: *P<.05, **P<.01

c) Multiple linear regression analysis

The results of multiple linear regression analysis demonstrated that the monthly income, age, and smoking status of the participants explained 12.5% of anti-smoking information scanning via social media (R^2=0 .125, F (5, 800) =22.860, p <.001) (as illustrated in table 4.10). Based on these analyses, the multiple linear regression model was shown as follows:

*Anti-smoking information scanning=0.211*income + 0.163* age -0.156* smoking status+ 3.592*

Table 4.10. Multiple linear regression analysis of participants' anti-smoking information scanning and four independent variables (income, age, gender, and smoking status)

Variables	B	β	P	VIF	Adjusted R^2
Income	0.211	0.221	.000	1.374	0.125
Gender	0.031	0.021	.555	1.200	
Age	0.163	0.152	.000	1.314	
Smoking status	-0.156	-0.109	.003	1.213	

2) Demographic effects on anti-smoking information scanning among smokers

a) Comparison analysis

By conducting One-way ANOVA tests among smokers, the differences in anti-smoking information scanning in age groups and income groups were observed, F (2, 456) =12.863, $p < .001$, F (2, 456) =9.631, $p < .001$, respectively. In contrast, there was no significant difference in the anti-smoking information scanning in gender and education groups (as shown in Table 4.11).

Table 4.11. One-way ANOVA tests on anti-smoking information scanning among smokers (N=459)

	Anti-smoking information scanning (Mean/± SD)	**F value**	***P***
Gender			
Female	4.14 (±0.56)	0.325	.744
Male	4.12 (±0.60)		
Age			
18-25	3.83 (±0.81)	12.863	.000
26-34	4.18 (±0.55)		
More than 35	4.21 (±0.54)		
Education			
High school graduate and below	4.16 (±0.63)	0.274	.601
College degree or above	4.12 (±0.57)		
Income			
Less than 4500 yuan	3.81 (±0.69)	9.631	.000
4501-8000 yuan	4.13 (±0.60)		
More than 8001 yuan	4.20 (±0.53)		

b) Correlation analysis

As displayed in Table 4.12, the results indicate that a positive correlation was found between age and smokers' anti-smoking information scanning behaviors, $\gamma(459) = 0.188,\ p < .001$. Similarly, strong evidence of the relationship between income and smokers' anti-smoking information scanning was observed, $\gamma(459) = 0.179,\ p < .001$. None of the remaining associations was significant.

Table 4.12 Pearson's correlation analysis of smokers' anti-smoking information scanning and four independent variables (income, education, age, and gender)

	Information scanning	**Age**	**Education**	**Income**	**Gender**
Information scanning					
Age	.188**				
Education	-.024	.186*			
Income	.179**	.308**	.257**		
Gender	.015	-.093*	.027	-.154**	

Note: significance level: *P<.05, **P<.01

c) Multiple linear regression analysis

The results of the multiple linear regression analysis are summarized in Table 4.13. It can be seen that income and age explained 5.5.% of the smokers' anti-smoking scanning, R^2=0.055, F (4, 454) =6.628, $p < .001$). And the regression model was constructed as follows:

*Anti-smoking information scanning=0.133*income + 0.127* age + 3.570*

Table 4.13. Multiple linear regression analysis of smokers' anti-smoking information scanning and four independent variables (income, age, gender, and education)

Variables	B	$\boldsymbol{\beta}$	P	VIF	Adjusted R^2
Income	0.133	0.155	.003	1.271	0.055
Gender	0.063	0.055	.253	1.030	
Age	0.127	0.137	.006	1.206	
Education	-0.061	-0.040	.418	1.171	

3) Demographic effects on anti-smoking information scanning among non-smokers

a) Comparison analysis

Table 4.14 illustrates the significant differences in non-smokers' anti-smoking information scanning in age groups ($F(2, 344) = 30.402$, $p < .001$) and income groups ($F(2, 344) = 25.779$, $p < .001$). There were no observed differences in gender groups or education groups.

Table 4.14. One-way ANOVA tests on anti-smoking information scanning among non-smokers (N=347)

	Anti-smoking information scanning (Mean/± SD)	**F value**	***P***
Gender			
Female	3.85 (±0.85)	1.189	.235
Male	3.98 (±0.74)		
Age			
18-25	3.41 (±0.87)	30.402	.000
26-34	4.12 (±0.69)		
More than 35	4.01 (±0.75)		
Education			
High school graduate and below	3.96 (±0.82)	0.365	.546
College degree or above	3.87 (±0.83)		
Income			
Less than 4500 yuan	3.38 (±0.85)	25.779	.000
4501-8000 yuan	3.96 (±0.76)		
More than 8001 yuan	4.13 (±0.73)		

b) Correlation analysis

Based on the results of the comparison analysis, further statistical tests revealed that non-smokers' age ($\gamma(347) = 0.303$, $p < .001$) and monthly income ($\gamma(347) = 0.342$, $p < .001$)

were significantly correlated to their anti-smoking information scanning via social media (Table 4.15).

Table 4.15. Pearson's correlation analysis of non-smokers' anti-smoking information scanning and four independent variables (income, education, age, and gender)

	Information scanning	**Age**	**Education**	**Income**	**Gender**
Information scanning					
Age	.303**				
Education	-.033	-.052			
Income	.342**	.508**	.157**		
Gender	-.064	-.048	.060	-.097	

Note: significance level: *P<.05, **P<.01

c) Multiple linear regression analysis

As shown in Table 4.16, non-smokers' income and age explained 13.4% of their anti-smoking behaviors (R^2=0.134, F (4, 342) =14.413, p < .001). Therefore, the multiple linear regression model was shown as follows:

*Anti-smoking information scanning=0.278*income + 0.200* age + 3.333*

Table 4.16. Multiple linear regression analysis of non-smokers' anti-smoking information scanning and four independent variables (income, age, gender, and education)

Variables	B	β	P	VIF	Adjusted R^2
Income	0.278	0.266	.000	1.426	0.134
Gender	-0.053	-0.026	.602	1.016	
Age	0.200	0.163	.006	1.381	
Education	-0.170	-0.064	.212	1.057	

4) Demographic effects on the total effect of anti-smoking information scanning

As shown in Table 4.17, no significant differences in the total effect of anti-smoking information scanning on anti-smoking behavior were found.

Table 4.17. Differences in the total effect of anti-smoking information scanning

	Total effect (β)	Diff.	*P*
Gender			
Female	0.222**	0.082	.083
Male	0.304**		
Age			
Younger [a]	0.217**	0.045	.332
Elder [b]	0.262**		
Income			
<8000	0.218**	0.065	.194
>8001	0.283**		
Education			
Lower [c]	0.323**	0.081	.178
Higher [d]	0.242**		
Smoking status			
Smoker	0.310**	0.087	.060
Non-smoker	0.223**		

Note: significance level: *P< .05, **P< .01

Younger [a]: ≤ 29 years old (N= 360)

Elder [b]: > 29 years old (N= 446)

Lower [c]: High school graduate and below (N=120)

Higher [d]: College degree or above (N=686)

CHAPTER 5

Study 3: Passive anti-smoking information acquisition via social media and anti-smoking behaviors in China: based on HBM and SIM model

5.1. Theoretical framework and Hypotheses

5.1.1. The establishment of a theoretical framework

As seen in Figure 5.1, the theoretical framework of the present study was developed based on the Health Belief Model and Structural Influence model of communication, both the most common models for exploring and predicting health outcomes.

To address the questions of the third study mentioned above, the association of social and individual factors, anti-smoking information scanning, and anti-smoking behaviors has been established according to prior conclusions derived from studies utilizing SIM. Moreover, as the primary outcome relates to anti-smoking behavioral changes, the present paper introduced the theories regarding the health belief model to offer a more comprehensive model to determine the mediators related to health perceptions between anti-smoking information exposure and anti-smoking behaviors among Chinese social media users. Therefore, in our proposed model, we considered not only positive emotions (i.e., perceived benefits and self-efficacy) and negative emotions (i.e., perceived barriers) but also threat appraisal (i.e., perceived severity and perceived susceptibility) (Lee et al., 2019).

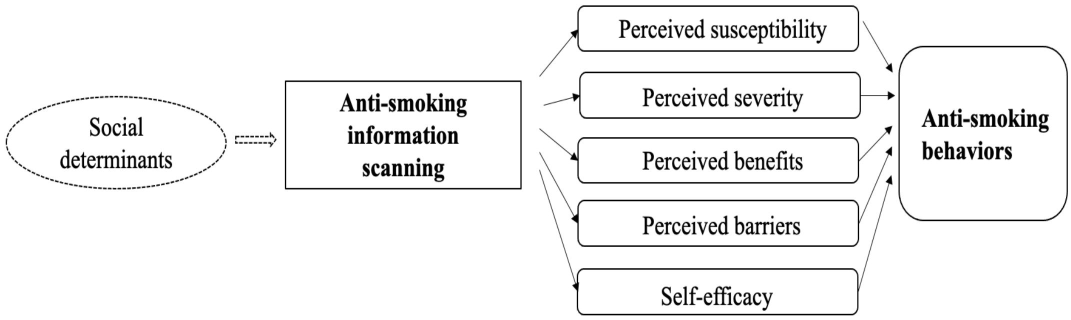


Figure 5.1. A theoretical framework based on HBM and SIM

5.1.2. Interpretation of constructs

According to the Structural Influence Model of communication, demographic parameters directly influence an individual's ability to access and seek information, in turn affecting health outcomes (Kontos & Viswanath, 2011). At this point, social determinants include socioeconomic position and socio-demographic characteristics. Socioeconomic position is defined as an individual's social resources and prestige, including the level of education, income, and employment status (Niederdeppe et al., 2008). Socio-demographic factors include age, gender, and race (Bigsby & Hovick, 2018).

Anti-smoking information scanning and anti-smoking behaviors have been illustrated in Chapter 4 (pp. 80-81). Evidence suggests that the core objectives of anti-smoking messages refer to ceasing smoking among current smokers and reducing smoking initiation among non-smokers (Yu et al., 2015). And anti-smoking information scanning refers to the passive receipt of anti-smoking messages. Anti-smoking behaviors of smokers refer to smoking cessation, relapse prevention, or decreased number of cigarettes smoked. For non-smokers, anti-smoking behaviors include smoking prevention and persuasion.

Previous studies have established that the measurement metrics of an individual's health attitudes include perceived susceptibility, perceived risk, perceived benefits, perceived barriers, and self-efficacy (Webel, 2015; Wisanti et al., 2020). Throughout this study, perceived susceptibility is used to refer to an individual's perceived threat of the chances of suffering from tobacco-related diseases, such as lung cancer and cardiovascular diseases. Perceived severity refers to a person's cognitions of the negative influence of tobacco-related diseases and other consequences of tobacco use in daily life (Lee et al., 2019; Renuka & Pushpanjali, 2014).

Additionally, the term perceived benefit is used to describe individuals' recognition of practical changes in general health and quality of life after taking advised action, while perceived barriers to taking this action are about an individual's opinions of the difficulties or costs of engaging anti-smoking behaviors (Abraham & Sheeran, 2005; Aryal & Bhatta, 2015).

Overall, previous studies categorized the barriers to anti-smoking into three types: a) internal barriers: such as losing a source of pleasure and losing of copping tool for stress; b) external barriers: difficulties caused by the social environment; and c) withdrawal symptoms caused by tobacco addiction (Asher et al., 2003). Meanwhile, previous studies grounded anti-smoking efforts primarily defined self-efficacy as an individual's belief or confidence that they can successfully execute desired anti-smoking behaviors or refrain from smoking in high-risk situations (Condiotte & Lichtenstein, 1981; Etter et al., 2000).

5.1.3. Research hypotheses

Recent studies have shown that repeatedly coming across key anti-smoking information, such as updated policies, specific knowledge, and warnings messages, can persuade an individual to make changes to recognize the importance and benefits of appropriate behaviors (Nogueira et al., 2017; Khandeparkar et al., 2021). In turn, factors influencing severe perceived barriers include lack of knowledge (Schilling et al., 2019). In the same vein, previous studies have found that either health information seeking or scanning can be positively associated with enacting and maintaining anti-smoking beliefs and behaviors (Upadhyay et al., 2019; Zhu, 2017). In addition, it has been shown that users who encounter more relevant information are more likely to gain confidence in overcoming the barriers of recommended action (Cho et al., 2021). Interestingly, previous research findings have demonstrated that anti-smoking content with warning messages could be more effective as a motivator for non-smokers (Shadel et al., 2019). Based on these results, we formulated the following hypotheses:

H1: Anti-smoking information scanning via social media is positively associated with an individual's favorable attitudes towards anti-smoking;

H1a: Anti-smoking information scanning via social media has a positive influence on perceived benefits;

H1b: Anti-smoking information scanning via social media has a positive influence on perceived susceptibility;

H1c: Anti-smoking information scanning via social media has a positive influence on perceived severity;

H1d: Anti-smoking information scanning via social media has positive influence on self-efficacy;

H1e: Lack of anti-smoking information can contribute to severe perceived barriers.

Drawn upon existing studies, explicit and favorable attitudes can exert beneficial effects against tobacco use and predict a wide range of successful anti-smoking campaigns adopt (Shahnazi, 2013; Street & Lacey, 2018). Although their impact varies among different socio-demographic groups and cultural contexts, each element has been evaluated as a critical antecedent of controlling tobacco use among both smokers and non-smokers. Most relevant to the current study, an individual's perceived benefits to quitting create a vantage point to promote smoking cessation behaviors, and perceived barriers to quitting is more relevant than perceived benefits (Alton et al., 2018; Mantler, 2013). Also, an individual with higher perceptions of smoking-related health risks and benefits of tobacco control is more likely to produce desirable health outcomes, especially in younger people and non-smokers (Aryal & Bhatta, 2015; Garey et al., 2019). Considering the health belief model, existing studies have shown that greater self-efficacy and lower barrier perceptions are construed as essential preconditions that can activate recommended anti-smoking behaviors (Kaufman et al., 2018; Zvolensky et al., 2018). Hence, we hypothesized:

H2: Greater beliefs can contribute to more health desirable behavioral outcomes relevant to anti-smoking among smokers and non-smokers;

H2a: An individual's perceptions of benefits are positively associated with the uptake of anti-smoking behaviors;

H2b: An individual's perceptions of severity are positively associated with the uptake of anti-smoking behaviors;

H2c: An individual's perceived susceptibility is positively associated with the uptake of anti-smoking behaviors;

H2d: Higher self-efficacy is positively associated with the uptake of anti-smoking behaviors;

H2e: Perceptions of barriers are negatively associated with the uptake of anti-smoking behaviors.

5.2. Methods

5.2.1. Questionnaire distribution

All data was collected from a self-administered questionnaire. The major advantage of using self-report data is that researchers can obtain a broad amount of information effectively. Additionally, the responses are independent of the intervention and interpretation of researchers (Chan, 2010). To achieve the study objectives, the criteria for selecting the respondents are as follows: a) at least 18 years of age and b) have the habit of accessing social media in daily life. To facilitate the data collection, the current questionnaire was written into Chinese. Before beginning the survey, written consent was presented to inform all participants that they were participating in an online survey related to smoking-related behaviors and social media usage. In addition, this anonymous survey can assure confidentiality and improve response rate and accuracy. Considering questionnaire distribution, the link was distributed through the Credamo, WeChat, Sina-microblog, QQ and Zhi Hu to cover more groups from a larger geographic area between November 1, 2021, to January 31, 2022. The questionnaire for this study was approved by the ethical committee of the University Institute of Lisbon (95/2021)(Annexes A).

5.2.2. Measurement

On the basis of the definitions mentioned above, this questionnaire used the validated items derived from previous studies, and we analyzed each item individually with the aim of ensuring reliability.

The first section consists of demographic profiles and social media use. Regarding socio-demographic, we accessed age (continuous), gender (1=female, 2=male), education levels

(1=less than middle school, 2=high school graduate, 3=college degree or above), and monthly income (yuan) that was coded into three scales (1= less than 4500, 2= 4501-8000, 3=8001 or more) (Xiao et al., 2015; Xu et al., 2017).

Regarding social media use, participants were asked questions from three aspects: 1) frequency: whether or not they regularly use social media in their daily routine and the average usage frequency (ranging from 1=never to 5=a few times per day) (Zhu, 2017); 2) the choice of anti-smoking information sources: which of the following channels has been more frequently used to obtain anti-smoking information (1=traditional media, 2=social media); and 3) the choice of social media platforms: which of the following social media platforms has been more frequently used to obtain anti-smoking information (1=WeChat official accounts, 2=Sina microblog, 3=TikTok).

We also asked about participants' smoking status to divide them into two groups: smokers and non-smokers. For smokers, we set up additional questions to measure the stage of tobacco use according to Fagerstrom Test for Nicotine Dependence (FTND). This test is widely available in most recent studies and has been developed to measure a smoker’s daily nicotine intake and physical nicotine dependence (Radzius et al., 2003; Vozoris & Stanbrook, 2011). One of the two main dimensions of access to nicotine addiction includes the number of cigarettes smoked per day (CPD) and the first cigarettes after waking up (TTF) (Heatherton et al., 1991). Hence, we asked smokers two questions, one was “how soon do you smoke your first cigarette after waking (3=in five minutes; 2=6-30 minutes; 1=31-60 minutes; 0=over 60 minutes), the other one is how many cigarettes you smoke each day (3=more than 31; 2=21-30; 1=11-20; 0= less than 10) (Salhi et al., 2021).

Finally, in this section, health literacy also was measured because it has been acknowledged to be associated with how people seek or encounter health information and how much they leverage or trust it (Zoellner et al., 2009). Therefore, in this section, participants are asked whether they have the confidence to read, obtain and process health information by themselves when using social media platforms (Waters, 2019). Also, the responses regarding self-rated health status were collected as it has been considered a predictive factor of social media usage for health purposes (Oh & Kim, 2014).

Then, it will go on to the assessment of anti-smoking information scanning behavior among the participants. Similarly, four questions were set up to measure the level of anti-smoking information scanning from three perspectives: depth, activeness, and breadth. The responses were rated based on a 5-point Likert scale (1=never, 5=very frequent).

To assess health attitudes towards tobacco use, we set up different questions for smokers and non-smokers. More notably, all these questions explicitly focused on the health-related risks and benefits for self rather than others (Li & Kay, 2009; Zlatev et al., 2010).

Among smokers, with respect to their perceptions of benefits and barriers regarding smoking cessation, the participants were asked to assume that they would stop smoking successfully in the future. Then, perceived benefits were accessed using two items regarding positive consequences (Sutton et al., 1990; Mckee et al., 2005). Similarly, regarding perceived severity, the participants were asked to evaluate how severe the negative health consequence of smoking-related diseases would be, followed by a 5-point Likert scale (1= hard matters at all, 5= matters a lot) (Ho, 1992; Kaufman et al., 2018).

The smokers' perceptions of barriers related to smoking cessation are measured based on the

Barriers to Quitting Smoking in Substance Abuse Treatment questionnaire (BQS-SAT), involving internal and external difficulties and withdrawal symptoms (Martin et al., 2016; McHugh et al., 2017). In this regard, participants were asked to indicate their level of agreement with these statements. Their responses were rated on a 5-point scale (1=strongly disagree, 5=strongly agree). Perceived susceptibility of smoking is measured using three items that assess smokers' concerns about getting smoking-related health illnesses, including lung cancer, heart diseases, and respiratory illnesses. Responses were given on a 5-point scale (1=worry not at all, 5=worry all of the time) (Li and Kay, 2009; Waters et al., 2016).

Four statements indicating anti-smoking self-efficacy were proposed according to the Smoking Abstinence Self-Efficacy Questionnaire (SASEQ), which rates the confidence of respondents on refraining from cigarettes in different social and emotional situations, ranging from 1(=certainly not) to 5 (= indeed) (Etter et al., 2000; Spek et al., 2013).

To measure the perceptions of non-smokers, the participants were asked to imagine they were exposed to second-hand smoke or are planning to initiate cigarette smoking (Aryal & Bhatta, 2015). In this way, their perceived benefits refer to the perceptions of health advantages of tobacco control (i.e., not smoking and protecting smoke-free environments) (Arens et al., 2014; Roszkowski et al., 2014). Like questions tailored to smokers, the perceptions of susceptibility and severity were assessed by asking them how much they worry about smoking-related diseases caused by second-hand smoke and its seriousness (Pancani & Rusconi, 2018; Yang et al., 2010).

And perceived barriers of non-smokers were measured using three items, including the difficulties in protecting themselves from second-hand smoke (i.e., too many smokers surrounding me, too embarrassed to prevent smoking in public places) and the concerns about the lack of identity or limiting social activities (Li & Kay, 2009; Lennon et al., 2005). Measures of self-efficacy among non-smokers include refusal self-efficacy in public spaces, self-refusal efficacy under specific emotional situations, and the confidence to persuade others (Mokhtari et al., 2013; Reisi et al., 2014). All their responses were rated based on the Likert 5-point scale.

Among the current smokers, smoking cessation behaviors can be measured by two aspects. The primary aspect refers to quit rates and prevalence rates; the second aspect refers to intermediate measures, including quit attempts, as well as the changes in knowledge and the number of daily cigarettes smoked or purchased (Bala et al., 2017; Naslund, 2016). In the present study, smoking cessation behaviors were assessed by single-item, measuring past attempts to quit, and their responses were followed by a 5-point scale (1=completely no, 5=completely yes) (Hyland et al., 2006; Luo et al., 2021). Similarly, among non-smokers, anti-smoking behaviors were measured using one item regarding whether they persuaded others to stop smoking in the past (Chang et al., 2006; Jiang & Beaudoin, 2016).

5.2.3. Data analysis

In the third study, two types of statistical analysis were utilized depending on previously proposed objectives. One is comparison analysis, and the other is correlation analysis. In the statistical domain, these two common measures accompany three statistical tests according to the number of targeted variables: univariate, bivariate, and multivariate (Denis, 2021). Both statistical analyses have been widely available and appropriate for quantitative measurement in social science disciplines ranging from communication, business, and human behaviors (Ong & Puteh, 2017).

As for comparison analysis, this involves quantifying the statistical differences across more than two independent groups towards one or more targeted variables, including the independent t-tests (one variable, two comparison groups) and the one-way analysis of variance (one-way ANOVA) (one variable, more than two comparison groups) (Larson, 2008; Lowry, 2014). Both statistical approaches require that the grouping variable (also known as the independent variable) has two or more groups, the measurement of the dependent variable is a ratio or interval, and the distribution of the dependent variable must coincide with a normal distribution (Park, 2009).

In statistical analysis, the Chi-square test of independence could be classified as a hypothesis testing method used in the past to determine the differences in the distribution of categorical variables among comparison groups (McHugh, 2013). In other words, the Chi-square test has been proposed to make a comparison between two or more categorical variables and assess their associations, but not examine casual relationships (Franke, 2012). Moreover, the Chi-square test requires a relatively large sample size, and the expected frequencies should be at least five for all the cells (Sharpe, 2015).

As for statistical correlation analysis, this includes Pearson' Correlation analysis, which has been employed to identify the bivariate relationship between two variables when the measurement of both variables is continuous, and the data fits the normal distribution (Bolboaca & Jäntschi, 2006). And multiple linear regression analysis is an appropriate method if the nature of all the variables is continuous and there have an analytic expression for the change in one dependent variable with more than one independent variable (Schobe et al., 2018). Hence, parametric tools include the independent t-test, one-way ANOVA, Pearson's correlation analysis as well as multiple linear regression analysis. At the same time, the Chi-square statistic could be classified as a non-parametric statistical method (Ong & Puteh, 2017).

Compared with the multiple linear regression analysis, it was considered that the structural equation modeling would usefully explore the causal and effect relationship involving several independent and dependent variables at a time. As mentioned earlier, PLE-SEM has become more suitable for conducting multivariate analysis in social science, internet, and communication research (Farooq et al., 2020; Shiau et al., 2019).

With that in mind, descriptive analysis was used to illustrate the participants' demographic characteristics, social media use, and smoking status. Next, the Chi-square test was chosen to help understand whether smoking characteristics vary among different socio-demographic groups. Here, in this aspect, the independent variables relate to gender, age, income, and education. Regarding dependent variables, this involves smoker types, the use of tobacco products, self-reported time to the first cigarette of the day (TTF), and the self-reported number of cigarettes smoked per day (CPD). Third, the independent t-test, one-way ANOVA, and Chi-square tests were used to explore whether the social media use of smokers differs according to socio-demographic factors and their smoking characteristics. As the dependent variables, the term social media use involves the frequency of social media use, the choice of anti-smoking information sources, and social media platforms. To facilitate the Chi-square tests and ensure the expected frequency is at least five in each cell of the table, the smokers were categorized into two age groups: 18 to 31 years old and over the age of 32 years old, and two income groups: over 8000 yuan a month and less than 8000 yuan a month, and two education levels: bachelor’s degree or above and high school graduate or below. Similarly, the smokers were categorized into two groups according to the time to their first cigarette after waking up (TTF): within 30 minutes and over 31 minutes. Finally, the smokers were divided into two sub-groups according to the number of cigarettes smoked per day: less than ten and more than ten.

Similarly, Chi-square tests and the independent t-tests were also adopted to capture whether the social media use of the non-smokers varies among different comparison subgroups. For Chi-square tests, the non-smokers were categorized into two age groups: 18 to 28 years old and over 29 years, and two education levels: bachelor's degree or above and high school graduate or below.

Then, the independent t-tests and Chi-square tests were undertaken to examine the significant differences in demographic factors, social media use, and the mean values of anti-smoking information scanning, perceived benefits, perceived barriers, perceived susceptibility, perceived severity, self-efficacy, and anti-smoking behaviors between smokers and non-smokers.

Concerning demographic effects on anti-smoking information scanning, one-way ANOVA, Pearson's correlation analysis, and multiple linear regression analysis were conducted among smokers and non-smokers. All analyses mentioned above were carried out using Statistical Package for Social Sciences (SPSS-version 26).

Then, adopting partial least squares structural equation modeling (PLS-SEM) is in accord with the objectives of this study, testing the proposed hypotheses regarding the indirect effect of anti-smoking information scanning on anti-smoking behaviors via health attitudes among smokers and non-smokers. Correspondingly, the methodological literature has revealed that applying PLS-SEM is appropriate for coping with well-established theories and highly complex models with rich and continuous data, especially examining mediating effects, which is the rationale for using this method for the present study (Hair et al., 2012; Reinartz et al., 2009). Additionally, the decision on PLS-SEM's application was based on data characteristics, sample size issues, and measurement items, that the sample consisted of more than 100 participants, the data is continuous and normally distributed, as well as at least one question was set up to measure the constructs. Data management and analysis were performed using Smart PLS 3.3.

The first step in this process is to check the reliability and validity of constructs, involving internal consistency, item reliability, convergent validity, and discriminant validity. The second step is to evaluate the proposed theoretical model by running complete bootstrapping (resampling 5000). The third set of analyses (Multigroup-analysis using partial least squares modeling, MGA) evaluates the existence of significant differences in path coefficients across groups. During data group generation, the data sample was divided into different subgroups according to socio-demographic factors and smoking characteristics, and similar sample sizes for each group were also considered. Before making group comparisons, measurement invariance was accessed by performing the measurement invariance of the composite model procedure (MICOM) (Cheah et al., 2020; Hair et al., 2021). Table 5.1 provides the summary of statistical analyses used in the current study.

Table 5.1. Statistical analyses adopted in the third study

	Objectives	**Independent variables**	**Dependent variables**	**Data analysis**	**Software**
1.	To examine whether socio-demographic variables impact smoking characteristics	a) gender b) age c) income d) education	a) smoker type b) cigarette use c) TTF d) CPD	Independent t-test One-way ANOVA	SPSS (26.0)

	and social media use of smokers.		e) frequency of social media use f) information sources c) social media platforms	Chi-square test	
2.	To examine how socio-demographic factors impact on social media use of non-smokers.	a) gender b) age c) income d) education	a) frequency of social media use b) information sources c) social media platforms	Independent t-test analysis One-way ANOVA Chi-square test	SPSS (26.0)
3.	To measure the significant differences between smokers and non-smokers towards different targeted variables	Smoker vs non-smoker	a) socio-demographic factors b) social media use c) health status d) health literacy e) anti-smoking information scanning f) health attitudes (perceived benefits, perceived barriers, perceived severity, perceived susceptibility, self-efficacy) g) anti-smoking behaviors	Independent t-test One-way ANOVA Chi-square test	SPSS (26.0)
4.	To determine the relationships between socio-demographic factors and anti-smoking	a) gender b) age c) income d) education	anti-smoking information scanning	Univariate comparison analysis Pearson's	SPSS (26.0)

	information scanning of the participants	e) health literacy f) health status		correlation analysis Multiple linear regression analysis	
5.	To test the causal relationship between independent and dependent variables	As shown in the proposed theoretical framework		Partial least squares structural equation modeling	Smart PLS 3.3
6.	To determine the existence of significant differences in path coefficients between different subgroups	As shown in the proposed theoretical framework		Multigroup analysis (MGA)	Smart PLS 3.3

5.3. Results

5.3.1. Descriptive analysis

1) Respondent Profile

The second column of Table 5.2 provides an overview of the socio-demographic characteristics of the participants. The sample consisted of 921 respondents, including 466 (50.5%) smokers and 455 (49.5%) non-smokers. Approximately half of the respondents were female (n=457, 49.6%). The average age of the participants was 31.10 (SD = ±5.28) among smokers and 28.41 (SD = ±6.53) among non-smokers. Most reported having more than a high school education (n=914, 99.3%). For income, 84% of the participants reported they earn over 4501 yuan (US$706) per month. Among 466 smokers, there were 128 females (27.5%) and 338 males

(72.5%). The vast majority of the smokers were between 26 and 44 years of age (n=404, 86.3%) and had bachelor's degrees or above (n= 423, 99.2%). In the sample, over half of the smokers reported making 8001 yuan (US$ 1255.1) a month (n=286, 61.4%). Out of the 455 non-smokers, their ages ranged from 18 to 56 years, and most participants were female (n=329, 72.3%). In addition, 452 non-smokers completed high school or above (99.4%), and 26.8% of the non-smokers reported having a monthly income of less than 4500 yuan (US$705.9). Mean scores of the other two variables were as follows: self-reported health status $_{(smoker)}$ (Mean=4.15, SD = ±0.55), self-reported health status $_{(smoker)}$ (Mean=4.21, SD = ±0.64), self-reported health literacy$_{(smoker)}$ (Mean=4.54, SD = ±0.54) and self-reported health literacy $_{(non\text{-}smoker)}$ (Mean=4.41, SD = ±0.66).

Table 5.2. Demographic distribution and background information of study participants (N=921)

Factors	**Total** (N=921)	**Smoker** (N=466)	**Non-smoker** (N=455)
Gender			
Female	457 (49.6%)	128 (27.5%)	329 (72.3%)
Male	464 (50.4%)	338 (72.5%)	126 (27.7%)
Age			
18-25	194 (21.0%)	52 (11.2%)	141 (31.0%)
26-34	576 (62.5%)	313 (67.2%)	263 (57.8%)
35-44	128 (13.9%)	91 (19.5%)	37 (8.1%)
More than 45	24 (2.6%)	10 (2.1%)	14 (3.1%)
Education			
Less than middle school	7 (0.7%)	4 (0.8%)	3 (0.6%)
High school graduate	104 (11.3%)	39 (8.3%)	65 (14.3%)
College degree or above	810 (87.9%)	423 (90.8%)	387 (85.1%)
Income			

Less than 4500 yuan	147 (16.0%)	25 (5.3%)	122 (26.8%)
4501-8000 yuan	338 (36.7%)	155 (33.3%)	183 (40.2%)
More than 8001 yuan	436 (47.3%)	286 (61.4%)	150 (33.0%)
Health status (Mean/±SD)	4.18 (±0.59)	4.15 (±0.55)	4.21 (±0.64)
Health literacy (Mean/±SD)	4.48 (±0.60)	4.54 (±0.54)	4.41 (±0.66)

2) Social media use of the participants

Among the 921 respondents recruited, the highest proportion of participants reported using social media platforms to get anti-smoking information. Table 5.3 shows that the average frequency of social media use is 4.46 (SD = ± 0.58) among smokers and 4.45 (SD = ± 0.66) among non-smokers. TikTok is the most popular social media in both groups, accounting for 48.7% of smokers and 40.4% of non-smokers. For smokers, ranked second and third were Sina microblog (31.5%) and WeChat official account (19.7%). Conversely, for non-smokers, the WeChat official account (30.3%) is more frequently used than the Sina microblog platform (29.2%).

Table 5.3. Social media use of the participants (N=921)

	All (N=921)	**Smoker** (N=466)	**Non-smoker** (N=455)
Frequency of social media use			
Mean (±SD)	4.45 (±0.62)	4.46 (±0.58)	4.45 (±0.66)
Which channel do you obtain anti-smoking information from more frequently?			
Traditional media	54 (5.9%)	19 (4.1%)	35 (7.7%)
Social media	867 (94.1%)	447 (95.9%)	420 (92.3%)
Which following platforms do you obtain anti-smoking information more frequently?			
TikTok	411 (44.6%)	227 (48.7%)	184 (40.4%)
Sina microblog	280 (30.4%)	147 (31.5%)	133 (29.2%)
WeChat official account	230 (25.0%)	92 (19.7%)	138 (30.3%)

3) Smoking characteristics of the smokers

It can be seen from the data in Table 5.4 that there were 160 everyday smokers (34.3%) and 306 someday smokers (65.7%). Most of the tobacco products smoked are regular cigarettes, accounting for 92.3%. 52.2% of the respondents reported that the time to the first cigarette after waking up ranged from 5 to 60 minutes. Additionally, Table 5.4 illustrates that 97% of the current smokers smoke fewer than 20 cigarettes daily.

Table 5.4. Smoking characteristics of the smokers (N=466)

	Distribution (%)
Smoker type	
"everyday smoker"	160 (34.3%)
"some day smoker"	306 (65.7%)
"Which type of cigarette are you used to smoke?"	
Regular cigarette	430 (92.3%)
E-cigarette/Water pipes/Cigar	36 (7.7%)
"How soon after you wake up do you smoke your first cigarette?" (TTF)	
Within 5 minutes	22 (4.7%)
5 to 30 minutes	127 (27.3%)
31 to 60 minutes	116 (24.9%)
After 60 minutes	201 (43.1%)
"How many cigarettes do you smoke each day?" (CPD)	
10 or fewer	279 (59.9%)
11 to 20	173 (37.1%)
21 to 30	14 (3.0%)
31 or more	0 (0%)

5.3.2. Comparison analysis among smokers

1) Demographic correlates of smoking characteristics

a) Demographic variables and smoker types

Chi-square tests indicated that males were significantly over-represented among everyday smokers, while females were more likely to be someday smokers, $\chi 2(1, N = 466) = 58.351, p < .001, \phi = .354, p < .001$. Also, significant differences were observed between the two age groups: everyday smokers were more likely to be younger participants, while more elder participants reported smoking occasionally, $\chi 2(1, N = 466) = 10.662, p < .151, \phi = .354, p < .001$.The results revealed that the differences in smoker types between the two income groups were statistically significant, and participants with higher income tend to smoke every day $\chi 2(1, N = 466) = 5.593, p < .05, \phi = .110, p < .05$. Specifically, there was no significant association between education level and smoker types (Table 5.5).

Table 5.5. Chi-square tests on smoker types among socio-demographic groups (N=466)

	Everyday smoker n (%)	Someday smoker n (%)	Chi-square	df	*P*
Gender					
Female	9 (5.6%)	119 (38.9%)	58.351	1	.001
Male	151 (94.4%)	187 (61.1%)			
Age					
18-31	73 (61.4%)	188 (45.6%)	10.662	1	.001
32+	87 (38.6%)	118 (54.4%)			
Income					
Less than 8000	50 (31.3%)	130 (42.5%)	5.593	1	0.05
Over 8001	110 (68.7%)	176 (57.5%)			
Education					

High school graduate or below	16 (10.0%)	27 (8.8%)	0.174	1	.677
Bachelor's degree or above	144 (90.0%)	279 (91.2%)			
Total	160 (34.3%)	306 (65.7%)			

b) Demographic variables and tobacco products

As shown in Table 5.6, there were differences in the use of tobacco products across gender, age groups, and income groups, while no other associations were significant. Moreover, the e-cigarette was more likely to feature females, $\chi2(1, N = 466) = 55.189, p < .001, \phi = .344, p < .001$. And more younger participants reported their habits of using e-cigarettes than the elder, $\chi2(1, N = 466) = 4.163, p < .05, \phi = .095, p < .05$. Also, the higher-income participants tend to use cigarettes or cigars $\chi2(1, N = 466) = 10.503, p < .001, \phi = .150, p < .001$.

Table 5.6. Chi-square tests on the use of tobacco products among socio-demographic groups (N=466)

	Regular cigarette n (%)	**E-cigarette/Water pipes n (%)**	**Chi-square**	**df**	***P***
Gender					
Female	99 (23.0 %)	29 (80.6%)	55.189	1	.001
Male	331 (77.0 %)	7 (19.4%)			
Age					
18-31	235 (54.7%)	26 (72.2%)	4.163	1	.001
32+	195 (45.3%)	10 (27.8%)			
Income					
Less than 8000	157 (36.5%)	23 (63.9%)	10.503	1	.001
Over 8001	273 (63.5%)	13 (36.1%)			

Education					
High school graduate or below	39 (9.1%)	4 (11.1%)	0.165	1	.684
Bachelor's degree or above	391(90.9%)	32 (88.9%)			
Total	430 (92.3%)	36 (7.7%)			

c) Demographic variables and TTF

As can be seen in Table 5.7, none of the associations between demographic variables (age, gender, income, and education) and the self-reported time to the first cigarette of the day (TTF) were significant.

Table 5.7. Chi-square tests on TTF among socio-demographic groups (N=466)

	Within 30 minutes n (%)	**Over 30 minutes n (%)**	**Chi-square**	**df**	***P***
Gender					
Female	34 (22.8%)	94 (29.7%)	2.376	1	.123
Male	115 (77.2%)	223 (70.3%)			
Age					
18-31	77 (51.7%)	184 (58.0%)	1.667	1	.197
32+	72 (48.3%)	133 (42.0%)			
Income					
Less than 8000	64 (43.0%)	116 (36.6%)	1.729	1	.188
Over 8001	85 (57.0%)	201 (63.4%)			
Education					
High school graduate or below	17 (11.4%)	26 (8.2%)	1.245	1	.265
Bachelor's degree or above	132 (88.6%)	291 (91.8%)			
Total	149 (32.0%)	317 (68.0%)			

d) Demographic variables and CPD

The number of cigarettes smoked per day (CPD) was significantly higher in males than in females, $\chi2(1, N = 466) = 28.844, p < .001, \phi = .249, p < .001$, as well as in elder participants than in younger participants $\chi2(1, N = 466) = 7.872, p < .01, \phi = .130, p < .01$. No significant differences between other groups were evident (see details in Table 5.8).

Table 5.8. Chi-square tests on CPD among socio-demographic groups (N=466)

	Less than 10 **n (%)**	**More than 10** **n (%)**	**Chi-square**	**df**	***P***
Gender					
Female	102 (36.6%)	26 (13.9%)	28.844	1	.001
Male	177 (63.4%)	161 (86.1%)			
Age					
18-31	171 (61.3%)	90 (48.1%)	7.872	1	.01
32+	108 (38.7%)	97 (51.9%)			
Income					
Less than 8000	112 (40.1%)	68 (36.4%)	0.675	1	.411
Over 8001	167 (59.9%)	119 (63.6%)			
Education					
High school graduate or below	27 (9.7%)	16 (8.6%)	0.168	1	.682
Bachelor's degree or above	252 (90.3%)	171 (91.4%)			
Total	279 (59.9%)	187 (30.1%)			

2) Demographic correlates of social media use among smokers

a) Demographic variables and the frequency of social media use

One-way analysis of variance tests and independent t-tests indicated that frequency of social media use was only significantly related to different educational levels, F (2, 466) =5.909, p= .003. Furthermore, respondents who reported a higher education level showed significantly higher social media use frequency. And Fisher LSD post hoc tests demonstrated that the participants with the lowest level of education also reported the lowest frequency of social media use than the other two groups, with a mean and standard deviation of 3.50 (± 0.58). Notably, there was no evidence that other demographic variables have an influence on smokers' frequency of social media use (as shown in Table 5.9).

Table 5.9. One-way ANOVA tests on the frequency of social media use among socio-demographic groups of smokers (N=466)

	Frequency of social media use Mean (±SD)	**F value**	***P***
Gender			
Female	4.52 (± 0.58)	0.1337	.182
Male	4.43 (± 0.57)		
Age			
18-25	4.42 (± 0.67)	0.932	.425
26-34	4.48 (± 0.57)		
35-44	4.43 (± 0.58)		
More than 45	4.20 (± 0.63)		
Education			
Less than middle school	3.50 (± 0.58)	5.909	. 003
High school graduate	4.54 (± 0.56)		
College degree or above	4.46 (± 0.58)		
Income			
Less than 4500 yuan	4.32 (± 0.69)	1.107	. 331
4501-8000 yuan	4.43 (± 0.61)		
More than 8001 yuan	4.48 (± 0.55)		

b) Demographic variables and the choice of anti-smoking information sources

Overall, the Chi-square tests did not show any significant differences in anti-smoking information sources between males and females, the younger and the elder, and the higher and lower income groups. Interestingly, as shown in Table 5.10, the participants who reported a higher level of education also reported relying more on social media platforms to obtain anti-smoking information than traditional media, $\chi 2(1, N = 466) = 11.814, p < .01, \phi = .159, p < .01$.

Table 5.10. Chi-square tests on the choice of anti-smoking information sources among socio-demographic groups of smokers (N=466)

	Traditional media n (%)	**Social media n (%)**	**Chi-square**	**df**	***P***
Gender					
Female	5 (26.3%)	123 (27.5%)	0.013	1	. 909
Male	14 (73.7%)	324 (72.5%)			
Age					
18-31	10 (52.6%)	251 (56.2%)	0.092	1	. 762
32+	9 (47.4%)	196 (43.8%)			
Income					
Less than 8000	9 (47.4%)	171 (38.3%)	0.639	1	. 424
Over 8001	10 (52.6%)	276 (61.7%)			
Education					
High school graduate or below	6 (31.6%)	37 (8.3%)	11.814	1	. 001
Bachelor’s degree or above	13 (68.4%)	410 (91.7%)			
Total	19 (4.1%)	447 (95.9%)			

c) Demographic variables and the choice of social media platforms

Regarding the preferences of which social media platform to use, as shown in Table 5.11, no evidence was found for significant differences across gender or age groups. However, monthly income and educational level were two predictors of the respondents' choice of social media platforms. On the one hand, the respondents with lower educational levels tend to use WeChat, whereas those with higher educational levels prefer using Sina microblog, $\chi 2(2, N = 466) = 8.810, p < .05, Cramer's\ V = .137\ p < .05$). On the other hand, the respondents with lower monthly income were more often to choose WeChat official accounts whereas higher income group were more likely to obtain anti-smoking information from Sina microblog platform via scanning $\chi 2(2, N = 466) = 6.883, p < .05, Cramer's\ V = .122\ p < .05$).

Table 5.11. Chi-square tests on the choice of social media platforms among socio-demographic groups of smokers (N=466)

	TikTok n (%)	**Sina microblog n (%)**	**WeChat n (%)**	**Chi-square**	**df**	***P***
Gender						
Female	63 (27.8%)	47 (32%)	18 (19.6%)	4.391	2	.111
Male	164(72.2%)	100 (68%)	74 (80.4%)			
Age						
18-31	122(53.7%)	88 (59.9%)	51 (55.4%)	1.371	2	.504
32+	105(46.3%)	59 (40.1%)	41 (44.6%)			
Income						
Less than 8000	92 (40.5%)	45(30.6%)	43(46.7%)	6.883	2	.032
Over 8001	135(59.5%)	102(69.4%)	49 (53.3%)			
Education						
High school graduate or below	23 (10.1%)	6 (4.1%)	14 (15.2%)	8.810	2	.012
Bachelor's degree or above	204(89.9%)	141(95.9%)	78 (84.8%)			

Total	227(48.7%)	147(31.5%)	92(19.7%)

3) The correlation of smoking characteristics and social media use among smokers

a) Smoking characteristics and frequency of social media use

In general, there were no observed differences in the frequency of social media use between different groups of smoking characteristics (see details in Table 5.12).

Table 5.12. Independent t-test on the frequency of social media among groups regarding smoking characteristics (N=466)

	Frequency of social media use Mean (± SD)	**F value**	***P***
Smoker types			
Every day smoker	4.45 (±0.59)	0.313	.755
Someday smoker	4.47 (±0.57)		
Tobacco products			
Cigarette/Cigar	4.44 (±0.58)	1.956	.051
E-cigarette/Water pipes	4.64 (±0.54)		
TTF			
Within 30 minutes	4.47 (0.55)	0.323	.747
Over 30 minutes	4.45 (0.60)		
CPD			
Less than 10	4.45 (0.59)	0.410	.682
More than 10	4.47 (0.56)		

b) Smoking characteristics and the choice of anti-smoking information sources

The results obtained from the Chi-square tests are displayed in Table 5.13, it is apparent that none of these comparison analyses were statistically significant.

Table 5.13. Chi-square tests on the choice of anti-smoking information sources among groups regarding smoking characteristics (N=466)

	Traditional media n (%)	**Social media n (%)**	**Chi-square**	**df**	***P***
Smoker types					
Every day smoker	8 (42.1%)	152 (34.0%)	0.530	1	.466
Someday smoker	11 (57.9%)	295 (66.0%)			
Tobacco products					
Cigarette/Cigar	16 (84.2%)	414 (92.6%)	1.807	1	.179
E-cigarette/Water pipes	3 (15.8%)	33 (7.4%)			
TTF					
Within 30 minutes	9 (47.4%)	140 (31.3%)	2.158	1	.142
Over 30 minutes	10 (52.6%)	307 (68.7%)			
CPD					
Less than 10	10 (52.6%)	269(60.2%)	0.432	1	.511
More than 10	9 (47.4%)	178 (39.8%)			

c) Smoking characteristics and the choice of social media platforms

As can be seen in Table 5.14, the choice of social media platforms was only significantly related to the choice of tobacco products, $\chi 2(2, N = 466) = 8.403, p < .05, Cramer's\ V = .134\ p < .05$). In this regard, the participants who reported using e-cigarette tend to use Sina microblog more frequently whereas the participants in the habit of using cigarette tend to use TikTok. None of the remaining differences were observed.

Table 5.14. Chi-square tests on the choice of social media platforms among groups regarding smoking characteristics (N=466)

	TikTok n (%)	**Sina microblog n (%)**	**WeChat n (%)**	**Chi-square**	**df**	***P***
Smoker types						

Every day smoker	78 (34.4%)	42 (28.6%)	40(43.5%)	5.577	2	.062
Someday smoker	149 (65.6%)	105 (71.4%)	52 (56.5%)			
Tobacco products						
Cigarette/Cigar	216 (95.2%)	128 (87.1%)	86 (93.5%)	8.403	2	.015
E-cigarette/Water pipes	11 (4.8%)	19 (12.9%)	6 (6.5%)			
TTF						
Within 30 minutes	72 (31.7%)	42 (28.6%)	35 (38.0%)	2.347	2	.309
Over 30 minutes	155(68.3%)	105 (71.4%)	57 (62.0%)			
CPD						
Less than 10	140 (61.7%)	89 (60.5%)	50 (54.3%)	1.503	2	.472
More than 10	87 (38.3%)	58 (39.5%)	42 (45.7%)			

5.3.3. Comparison analysis among non-smokers

1) Demographic correlates of social media use among non-smokers

a) Demographic variables and the frequency of social media use

As shown in Table 5.15, the one-way analysis of variance tests revealed that demographic variables were not significantly related to non-smokers' frequency of social media use.

Table 5.15. One-way ANOVA test on the frequency of social media use among socio-demographic groups of non-smokers (N=455)

	Frequency of social media use Mean (±SD)	**F value**	***P***
Gender			
Female	4.39 (±0.68)	1.238	.217
Male	4.47 (±0.65)		
Age			
18-25	4.35(±0.77)	2.409	.066

26-34	4.51(±0.58)		
35-44	4.35(±0.72)		
More than 45	4.57 (±0.65)		
Education			
Less than middle school	5.00 (±0.00)	1.076	.342
High school graduate	4.43 (±0.66)		
College degree or above	4.45 (±0.66)		
Income			
Less than 4500 yuan	4.42 (±0.79)	2.023	.133
4501-8000 yuan	4.52 (±0.55)		
More than 8001 yuan	4.39 (±0.65)		

b) Demographic variables and the choice of anti-smoking information sources

The Chi-square tests (see Table 5.16) demonstrated that the difference between the two age groups was significant $\chi 2(1, N = 455) = 4.490, p < .05, \phi = .099, p < .05$. The results revealed that the elder participants (over 29 years old) prefer using social media as anti-smoking information sources over the younger. Additionally, post hoc comparison tests indicated that non-smokers with higher monthly income tend to use social media platforms rather than traditional media, $\chi 2(2, N = 455) = 22.520, p < .001, Cramer's\ V = .222\ p < .001$. None of the remaining differences were evident.

Table 5.16. Chi-square tests on the choice of anti-smoking information sources among socio-demographic groups of non-smokers (N=455)

	Traditional media n (%)	**Social media n (%)**	**Chi-square**	**df**	***P***
Gender					
Female	29 (82.9%)	300 (71.4%)	2.107	1	.147
Male	6 (17.1%)	120 (28.6%)			

Age					
18-28	25 (71.4%)	222 (52.9%)	4.490	1	.034
29+	10 (28.6%)	198 (47.1%)			
Income					
Less than 4500	21 (60.0%)	101(24.0%)	22.520	2	.000
4501-8000	5 (14.3%)	178 (42.4%)			
Over 8001	9 (25.7%)	141 (33.6%)			
Education					
High school graduate or below	9 (25.7%)	59 (14%)	3.459	1	.063
Bachelor's degree or above	26 (74.3%)	361(86%)			

c) Demographic variables and the choice of social media platforms

It can be seen from Table 5.17 that no significant differences between females and males or the younger and the elder were statistically significant. However, the results indicate that the lowest income group (less than 4500 yuan) prefers using WeChat official accounts, whereas the middle-income group (4501-8000 yuan) is more likely to use TikTok, $\chi 2(2, N = 455) = 15.503, p < .01, Cramer's\ V = .131\ p < .01$. Besides, post hoc analysis demonstrated that non-smokers with lower educational level tend to use TikTok more often while the participants with higher educational level tend to use Sina microblog platform, $\chi 2(2, N = 455) = 7.680, p < .05, Cramer's\ V = .130\ p < .05$.

Table 5.17. Chi-square tests on the choice of social media platforms among socio-demographic groups of non-smokers (N=455)

	TikTok n (%)	**Sina microblog n (%)**	**WeChat n (%)**	**Chi-square**	**df**	***P***
Gender						

Female	131(39.8%)	101(30.7%)	97(29.5%)	1.271	2	.530
Male	53 (42.1%)	32 (25.4%)	41 (32.5%)			
Age						
18-28	96 (38.9%)	72 (29.1%)	79 (32.0%)	0.819	2	.664
29+	88 (42.3%)	61 (29.3%)	59 (28.4%)			
Income						
Less than 4500	38 (31.1%)	33 (27.0%)	51 (41.8%)	15.503	2	.004
4501-8000	88 (48.1%)	47 (25.7%)	48 (26.2%)			
Over 8001	58 (38.7%)	53 (35.3%)	39 (26.0%)			
Education						
High school graduate or below	37 (54.4%)	12(17.6%)	19 (27.9%)	7.680	2	.021
Bachelor's degree or above	147(38.0%)	121(31.3%)	119(30.7%)			

5.3.4. Comparison analysis between non-smokers and smokers

Before conducting comparison analyses between non-smokers and smokers, the internal consistency was measured as well in order to identify the reliability of the questionnaire. Regarding the questionnaire targeting smokers, the Cronbach's Alpha for four constructors was calculated as follows: anti-smoking information scanning consisted of three items (Cronbach alpha= .71), perceived barriers consisted of three items (Cronbach alpha= .83), perceived susceptibility consisted of three items (Cronbach alpha= .74) and self-efficacy consisted of three items (Cronbach alpha= .79). Regarding the questionnaire targeting non-smokers, the Cronbach's Alpha for four constructs was calculated as follows: anti-smoking information scanning consisted of three items (Cronbach alpha= .82), perceived barriers consisted of two items (Cronbach alpha= .72), perceived susceptibility consisted of three items (Cronbach alpha= .72) and self-efficacy consisted of two items (Cronbach alpha= .73). Consequently, all the values of Cronbach's alpha for the present study's sample were over 0.7 that were considered acceptable internal consistency (Taber, 2018).

1) Differences in socio-demographic variables between smokers and non-smokers

The results of Chi-square tests, as shown in Table 5.18, demonstrated males were significantly over-represented among current smokers, $\chi2(1, N = 921) = 185.162, p < .001, \phi = .448, p < .001$. In addition, the difference between the four age groups was also evident, $\chi2(3, N = 921) = 68.708, p < .001, Cramer's\ V = .273\ p < .001$ .Post-hoc analysis indicated that participants aged 35 to 44 years tend to smoke, whereas participants aged 25 and below are less likely to be a smoker. Specifically, the participants with higher educational levels are more likely to be smokers, $\chi2(1, N = 921) = 7.100, p < .01, \phi = .088, p < .01$. Also, the participants with higher monthly income were more likely to be smokers, while the participants with monthly income between 4501 and 8000 yuan were less likely to be smokers, $\chi2(2, N = 921) = 108.632, p < .001, Cramer's\ V = .343\ p < .001$.

Table 5.18. Chi-square tests on socio-demographic factors between smokers and non-smokers

	Smoker (%)	Non-smoker (%)	Chi-square	df	*P*
Gender					
Female	27.5%	72.3%	185.162	1	.000
Male	72.5%	27.7%			
Age					
18-25	11.2%	31.0%	68.708	3	.000
26-34	67.2%	57.8%			
35-44	19.5%	8.1%			
More than 45	2.1%	3.1%			
Education					

High school graduate or below	9.2%	61.3%	7.100	1	.008
Bachelor's degree or above	90.8%	47.8%			
Income					
Less than 4500 yuan	5.3%	26.8%	108.632	2	.000
4501-8000 yuan	33.3%	40.2%			
More than 8001 yuan	61.4%	33.0%			

2) Differences in social media use between smokers and non-smokers

a) Differences in the frequency of social media use between smokers and non-smokers

The independent t-test found no significant differences in mean scores on the frequency of social media use between smoker and non-smoker groups (see details in Table 5.19).

Table 5.19. The independent t-test on the frequency of social media use between smokers and non-smokers

	Smoker	**Non-smoker**	**T value**	***P***
Frequency (Mean/±SD)	4.46 (±0.58)	4.45 (±0.66)	.159	.873

b) Differences in anti-smoking information sources between smokers and non-smokers

As shown in Table 5.20, there was a significant difference in the choice of anti-smoking information sources, and smokers reported using social media more frequently, $\chi 2(1, N = 921) = 5.451, p < .05, \phi = .077, p < .05$.

Table 5.20. Chi-square test in the choice of anti-smoking information sources between smokers and non-smokers

	Smoker (%)	Non-smoker (%)	Chi-square	df	*P*
Traditional media	4.1%	7.7%	5.451	1	.020
Social media	95.9%	92.3%			

c) Differences in the choice of social media platforms between smokers and non-smokers

There was an observed difference in the choice of social media platforms between smoker and non-smoker groups, $\chi 2(2, N = 921) = 14.269, p < .01, Cramer's\ V = .124, p < .01$. The results of post-hoc tests revealed that smokers tend to use TikTok rather than WeChat official accounts to obtain anti-smoking information (as shown in Table 5.21).

Table 5.21. Chi-square test on the choice of social media platforms between smokers and non-smokers

	Smoker (%)	Non-smoker (%)	Chi-square	df	*P*
TikTok	48.7%	40.4%	14.269	2	.001
Sina microblog	31.5%	29.2%			
WeChat official account	19.7%	30.3%			

3) Differences in the mean values of self-reported health status and health literacy between smokers and non-smokers

Obviously, the independent t-test indicated that the mean values of health literacy between smoker and non-smoker groups differed significantly, *t* (893.9) =3.104, p < .01, but the two groups did not significantly differ in the mean scores of self-reported health status (see details in Table 5.22).

Table 5.22. The independent t-test on the mean of health status and health literacy between smokers and non-smokers

	Smoker	**Non-smoker**	**T value**	***P***
Health status (Mean/±SD)	4.15 (±0.55)	4.21 (±0.64)	1.651	.099
Health literacy (Mean/±SD)	4.54 (±0.54)	4.41 (±0.66)	3.104	.002

4) Differences in anti-smoking information scanning between smokers and non-smokers

It can be seen in Table 5.23, non-smokers (*M*=2.47, *SD*= ± 0.36) reported more exposure of anti-smoking information scanning than smokers (*M*=2.40, *SD*= ± 0.32), t (899.8) = 3.263, p <.01.

Table 5.23. The independent t-test on the mean of anti-smoking information scanning between smokers and non-smokers

	Smoker	**Non-smoker**	**T value**	***P***
Anti-smoking information scanning (Mean/±SD)	2.40 (±0.32)	2.47 (±0.36)	3.263	.001

5) Differences in the mean values of health attitudes related to anti-smoking between smokers and non-smokers

The results obtained from the independent t-tests are presented in Table 5.24. The smokers compared to the non-smokers demonstrated significantly higher mean scores of perceived barriers, t (837.9) = 17.139, $p < .001$, perceived susceptibility, t (797.8) = 28.498, $p < .001$, perceived severity, t (847.4) = 4.077, $p < .001$, and self-efficacy, t (848.4) = 7.137, $p < .001$.

Table 5.24. The independent t-tests on the mean of health attitudes regarding anti-smoking between smokers and non-smokers

	Smoker (Mean/±SD)	**Non-smoker (Mean/±SD)**	**T value**	***P***
Perceived benefits	4.14 (± 0.72)	4.17 (± 0.85)	0.429	.623
Perceived barriers	2.75 (± 0.42)	2.18 (± 0.57)	17.139	.000
Perceived susceptibility	3.09 (± 0.39)	2.18 (± 0.57)	28.498	.000
Perceived severity	4.50 (± 0.58)	4.32 (± 0.76)	4.077	.000
Self-efficacy	3.45 (± 0.36)	3.25 (± 0.47)	7.137	.000

6) Differences in anti-smoking behaviors between smokers and non-smokers

Mean differences in anti-smoking behaviors between the two groups were significantly observed, and smokers reported higher mean scores of anti-smoking behaviors, t (858.7) = 5.778, $p < .001$ (see Table 5.25),

Table 5.25. The independent t-test on the mean of anti-smoking behaviors between smokers and non-smokers

	Smoker	**Non-smoker**	**T value**	***P***
Anti-smoking behaviors (Mean/± SD)	4.23 (± 0.72)	3.91 (± 0.92)	5.778	.000

5.3.5. Demographic effects on anti-smoking information scanning

1) Demographic effects on anti-smoking information scanning among smokers

a) Comparison analysis

A one-way ANOVA revealed that the mean scores of anti-smoking information scanning were significantly different across four age groups, F (3, 466) =10.403, $p < .001$, three education groups, F (2, 466) =7.678, $p < .01$, and three income groups, F (2, 466) =14.968, $p < .001$.

None of the remaining analyses was evident (as shown in Table 5.26).

Table 5.26. One-way ANOVA tests on anti-smoking information scanning among socio-demographic groups of smokers (N=466)

	Anti-smoking information scanning (Mean/± SD)	**F value**	***P***
Gender			
Female	4.20 (±0.64)	0.746	.456
Male	4.16 (±0.62)		
Age			
18-25	3.79 (±0.82)	10.403	.000
26-34	4.20 (±0.59)		
35-44	4.31 (±0.48)		
More than 45	3.77 (±0.99)		
Education			
Less than middle school	3.75 (±0.96)	7.678	.001
High school graduate	3.82(±0.88)		
College degree or above	4.20 (±0.59)		
Income			
Less than 4500 yuan	3.56 (±0.93)	14.968	.000
4501-8000 yuan	4.13 (±0.61)		
More than 8001 yuan	4.24 (±0.57)		

b) Correlation analysis

According to the results from the abovementioned comparison analyses, three of four socio-demographic characteristics were identified as predictors of anti-smoking information scanning. Afterward, the results of Pearson's correlation analysis revealed that monthly income, age, and educational level were weakly correlated to mean scores of anti-smoking information scanning, $\gamma(466) = 0.208,\ p < .001$, $\gamma(466) = 0.338,\ p < .001$, and $\gamma(466) = 0.175,\ p < .001$

respectively. In addition, self-reported health status and health literacy were also positively correlated to anti-smoking information scanning, $\gamma(466) = 0.225,\ p < .001$ and $\gamma(466) = 0.258,\ p < .001$ respectively (see details in Table 5.27).

Table 5.27. Pearson's correlation analysis of smokers' anti-smoking information scanning and five independent variables (income, education, age, health status, and health literacy)

	Income	**Education**	**Age**	**Information scanning**	**Health status**	**Health literacy**
Income						
Education	.311**					
Age	.338**	-.066				
Information scanning	.208**	.175**	.338**			
Health status	.120**	.035	-.061	.225**		
Health literacy	.167**	.160**	.050	.258**	.115*	

Note: significance level: *P< .05, **P< .01

c) Multiple linear regression analysis

After dropping the insignificant variables based on the first two sets of analyses, the results of regression analysis revealed that education, age, health status, and health literacy explained 14.1% of the results on anti-smoking information scanning (R^2= 0 .141, F (5, 460) =16.248, $p < .001$). Despite the fact that income was found to be reactive to scanning information acquisition, it did not contribute to the multiple regression model. It can be seen in Table 5.28 that the multiple linear regression model was constructed as follows:

*Anti-smoking information scanning=0.225*education level + 0.219* age + 0.219* health status + 0.237* health literacy + 1.060*

Table 5.28. Multiple linear regression analysis of smokers' anti-smoking information scanning and five independent variables (income, education, age, health status, and health literacy)

Variables	B	***β***	*P*	VIF	Adjusted R^2
Income	0.079	0.075	.127	1.295	0.141
Education	0.225	0.118	.011	1.149	
Age	0.129	0.127	.006	1.143	
Health status	0.219	0.193	.000	1.030	
Health literacy	0.237	0.204	.000	1.053	

2) Demographic effects on anti-smoking information scanning among non-smokers

a) Comparison analysis

As can be seen in Table 5.29, there was a significant difference in mean scores of anti-smoking information scanning between age groups, F (2, 455) =39.923, $p < .001$, and income groups, F (3, 455) =13.457, $p < .001$. The test did not show significant differences between males and females, nor among three educational levels.

Table 5.29. One-way ANOVA tests on anti-smoking information scanning among socio-demographic groups of non-smokers (N=455)

	Anti-smoking information scanning (Mean/±SD)	**F value**	***P***
Gender			
Female	3.81 (±0.90)	.696	.486
Male	3.88 (±0.88)		
Age			
18-25	3.46 (±0.89)	13.457	.000
26-34	4.02 (±0.82)		
35-44	3.89 (±1.01)		
More than 45	3.81 (±0.86)		
Education			

Less than middle school	5.00 (±0.00)	2.586	.076
High school graduate	3.84 (±0.79)		
College degree or above	3.82 (±0.91)		
Income			
Less than 4500 yuan	3.26 (±0.91)	39.923	.000
4501-8000 yuan	4.02 (±0.75)		
More than 8001 yuan	4.06 (±0.85)		

b) Correlation analysis

As shown in Table 5.30, four variables were reactive to anti-smoking information scanning, including age, income, health status, and health literacy. Firstly, the results indicated that an increase in monthly income was concomitant with an increase in exposure to anti-smoking information during the routine use of social media, $\gamma(455) = 0.335,\ p < .001$. Also, age was predictive of the increase in anti-smoking information scanning, $\gamma(455) = 0.192,\ p < .001$. Additionally, a positive correlation between health status and anti-smoking information scanning was remained, $\gamma(455) = 0.358,\ p < .001$. And self-reported health literacy was also significantly correlated to scanning information acquisition among non-smokers, $\gamma(455) = 0.393,\ p < .001$.

Table 5.30. Pearson's correlation analysis of non-smokers' anti-smoking information scanning and six independent variables (age, income, education, gender, health status, and health literacy)

	Gender	**Education**	**Income**	**Health status**	**Health literacy**	**Information scanning**	**Age**
Gender							
Education	-.073						
Income	-.040	.168**					
Health status	-.124**	.019	.196**				

Health literacy	-.014	.091	.288**	.245**		
Information scanning	-.033	-.046	**.335****	**.358****	**.393****	
Age	.049	-.007	.424**	.065	.141**	**.192****

Note: significance level: $^*P< .05$, $^{**}P< .01$

c) Multiple linear regression analysis

Strong evidence was that health status, health literacy, and income were the significant explanatory variables. These three variables explained 26.9% of the variance in anti-smoking information scanning (R^2=0.269, F (4, 450) =41.307, $p < .001$). And the results also revealed that age did not contribute to the multiple regression model. Consequently, as can be seen in Table 5.31, the regression model obtained was given as follows:

Anti-smoking information scanning= 0.211 income + 0.352* health status + 0.367* health literacy + 0.153*

Table 5.31. Multiple linear regression analysis of smokers' anti-smoking information scanning and four independent variables (income, age, health status, and health literacy)

Variables	B	β	*P*	VIF	Adjusted R^2
Income	0.211	0.182	.000	1.328	0.269
Age	0.077	0.060	.179	1.220	
Health status	0.352	0.252	.000	1.085	
Health literacy	0.367	0.270	.000	1.137	

5.3.6. Hypotheses testing

1) Among smokers

a) Measurement model results

After dropping five items from anti-smoking information scanning, perceived benefits, perceived severity, and self-efficacy due to its outer loadings and composite reliability below 0.7, the reliability results are displayed in Table 5.32. It can be seen that all outer loadings and the composite reliability of each construct exceeded 0.7, and the value of AVE satisfied the recommended thresholds. Moreover, the values of VIF ranged from 1.000 to 1.818, which were well less than the threshold of 0.5. The discriminant validity results are shown in Table 5.33 and 5.34 based on the Fornell-Larcker and Heterotrait-Monotrait criteria. With these assessments, we ascertained that our data achieved excellent validity and reliability.

Table 5.32. The assessment of reliability and validity of the proposed model based on SIM and HBM (among smokers)

Construct, measurement item		Loading	VIF
Anti-smoking information scanning (CR:0.842; AVE:0.641)			
IN01	How often have you encountered information about anti-smoking on social media platforms?	0.838	1.591
IN02	How often do you ever read about posts that focus on anti-smoking information from diverse social media platforms, even if you don't subscribe to them?	0.733	1.280
IN03	Have you ever been exposed to such health segments regarding anti-smoking on social media when you were not trying to find out?	0.827	1.510
IN04	Can you remember any anti-smoking information obtained unintentionally during the routine use of social media?	-	-
Perceived benefit (CR:1.000; AVE:1.000)			
PBE01	Quitting smoking will lower my chances of developing lung cancer or heart disease.	1.000	1.000
PBE02	Quitting smoking will make me feel more energetic and become healthier.	-	-
Perceived barriers (CR:0.898; AVE:0.746)			
PBA01	If I quit smoking, I would miss out on a lot of fun	0.864	1.809

PBA02	If I quit smoking, I would feel hungry more often or eat more	0.845	1.863
PBA03	It is hard to quit smoking as so many others around me are smoking	0.881	2.140
Perceived susceptibility (CR:0.852; AVE:0.657)			
PSU01	Do you worry about you will get lung cancer?	0.781	1.516
PSU02	Do you worry about the increased risk of developing heart disease in your life?	0.836	1.543
PSU03	Do you worry about the increased risk of getting respiratory illnesses?	0.814	1.396
Perceived severity (CR:1.000; AVE:1.000)			
PSE01	How serious are tobacco-related diseases?	1.000	1.000
PSE02	How seriously does tobacco use cause respiratory problems?	-	-
PSE03	How seriously does tobacco use cause lung cancer?	-	-
Self-efficacy (CR:0.882; AVE:0.713)			
SE01	Someone offers you a cigarette of your brand. Are you confident that you will not smoke?	0.838	1.722
SE02	You feel agitated. Are you confident that you will not smoke?	0.852	1.818
SE03	You are in a café, at a party, or paying a visit. Are you confident that you will not smoke?	0.844	1.625
SE04	You see someone enjoy smoking. Are you confident that you will not smoke?	-	-
Smoking cessation behaviors (CR:1.000; AVE:1.000)			
B01	Have you ever attempted to quit smoking?	1.000	1.000

Table 5.33. Discriminant validity tests result using the Fornell-Larcker criterion (among smokers)

	Behavior	IN	PBA	PBE	PSE	PSU	SE
Behavior[a]	1.000	-	-	-	-	-	-
IN[b]	0.252	0.801	-	-	-	-	-
PBA[c]	-0.167	-0.254	0.864	-	-	-	-
PBE[d]	0.204	0.287	-0.336	1.000	-	-	-
PSE[e]	0.249	0.196	-0.258	0.249	1.000	-	-
PSU[f]	0.237	0.452	-0.330	0.319	0.444	0.811	-

SE[g]	0.315	0.347	-0.666	0.363	0.246	0.448	0.845

[a] Behavior: quit attempting to smoking

[b] IN: anti-smoking information scanning

[c] PBA: perceived barrier

[d] PBE: perceived benefit

[e] PSE: perceived severity

[f] PSU: perceived susceptibility

[g] SE: self-efficacy

Table 5.34. Discriminant validity tests result using the Heterotrait-Monotrait criterion (among smokers)

	Behavior	**IN**	**PBA**	**PBE**	**PSE**	**PSU**	**SE**
Behavior[a]	-	-	-	-	-	-	-
IN[b]	0.298	-	-	-	-	-	-
PBA[c]	0.181	0.326	-	-	-	-	-
PBE[d]	0.204	0.337	0.368	-	-	-	-
PSE[e]	0.249	0.230	0.280	0.249	1.000	-	-
PSU[f]	0.271	0.613	0.410	0.364	0.444	0.514	-
SE[g]	0.352	0.452	0.824	0.403	0.246	0.247	0.570

[a] Behavior: quit attempting to smoking

[b] IN: anti-smoking information scanning

[c] PBA: perceived barrier

[d] PBE: perceived benefit

[e] PSE: perceived severity

[f] PSU: perceived susceptibility

[g] SE: self-efficacy

b) Structural model results

Overall, the components explain 14.4% of the variance in anti-smoking behaviors of smokers. Moreover, the proposed model explained 8.2% of the variation in perceived benefits, 6.4% of perceived barriers, 20.4% of perceived susceptibility, 3.8% of perceived severity, and 12% of self-efficacy.

The empirical results indicated a significant and direct relationship between anti-smoking information scanning and health perceptions. As Table 5.35 shows, eight out of the ten hypothesized relationships were evident. As postulated, anti-smoking information scanning is positively associated with perceived benefits ($\beta = 0.287, p < .001$), perceived severity ($\beta = 0.196, p < .001$), perceived susceptibility ($\beta = 0.452, p < .001$), and self-efficacy ($\beta = 0.347, p < .001$). Also, a negative correlation was found between anti-smoking information scanning and perceived barriers ($\beta = -0.254, p < .001$). Therefore, H1 was supported.

Next, three constructs regarding smokers' health perceptions were found to affect anti-smoking behaviors significantly, including perceived barriers ($\beta = -0.121, p < .05$), perceived severity ($\beta = 0.168, p < .001$), and self-efficacy ($\beta = 0.308, p < .001$). Taken together, these results suggest that anti-smoking information scanning exerts an indirect influence on anti-smoking behaviors via perceived barriers, perceived severity, and self-efficacy ($\beta = 0.149, p < .001$) (Figure 5.2). In contrast, neither perceived benefit nor perceived susceptibility mediates the association between anti-smoking information scanning and anti-smoking behaviors.

Table 5.35. Results of hypotheses testing, path coefficients, t-statistics, f^2 value, and p-values (among smokers)

Hypothesis	Relationship	$\boldsymbol{\beta}$	T-value	*P*	f^2
H1a	IN and PBE	0.287	5.286	.000	0.090
H1e	IN and PBA	-0.254	5.127	.000	0.069
H1b	IN and PSE	0.196	3.752	.000	0.040
H1c	IN and PSU	0.452	8.959	.000	0.256
H1d	IN and SE	0.347	7.860	.000	0.137

H2a	PBE and B	0.079	1.595	.111	0.006
H2e	PBA and B	-0.121	2.087	.037	0.009
H2b	PSE and B	0.168	3.573	.000	0.026
H2c	PSU and B	0.039	0.645	.516	0.001
H2d	SE and B	0.308	4.634	.000	0.054

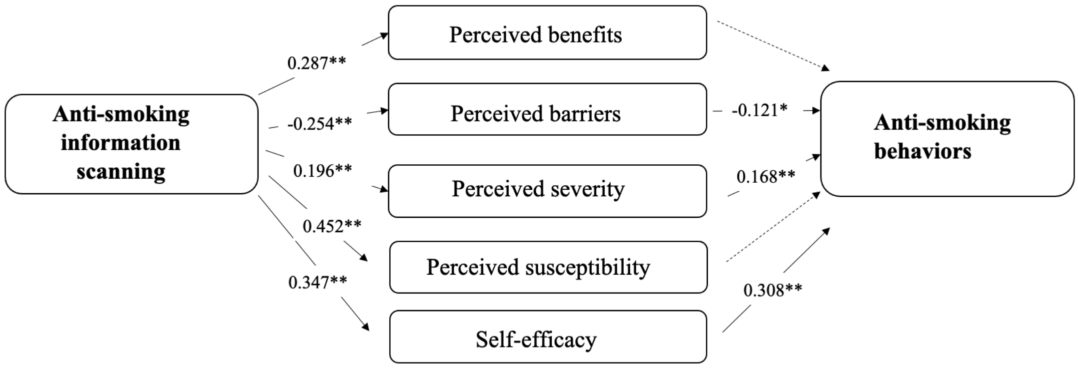


Figure 5.2. Path coefficients of the proposed relationships (among smokers)

Note: significance level: *P< .05, **P< .01

2) Among non-smokers

a) Measurement model results

As mentioned above, the item reliability, internal consistency, convergent validity, discriminant validity, and multicollinearity should be assessed before evaluating the structural model. For these purposes, seven items from anti-smoking information scanning, perceived benefits, perceived barriers, perceived severity, and self-efficacy were deleted, respectively, due to their item loadings below the minimum criterion. As shown in Table 5.36, the values of factor loadings and the composite reliability ranged from 0.749 to 1.000 and 0.836 to 1.000, respectively, which met the accepted threshold values of 0.7. Meanwhile, the value of AVE and VIF also were considered acceptable. Then, the discriminant validity results were then presented in Table 5.37 and 5.38, using the Fornell-Larcker and Heterotrait-Monotrait criterion. In particular, all HTMT scores exceeded 0.85 (for details, shown in Table 5.38). Overall, there was empirical evidence that our model and data were reliable and with a significant level of validity.

Table 5.36. The assessment of reliability and validity of the proposed model based on SIM and HBM (among non-smokers)

Construct, measurement item		Loading	VIF
Anti-smoking information scanning (CR:0.896; AVE:0.741)			
IN01	How often have you encountered information about anti-smoking on social media platforms?	0.889	2.138
IN02	How often do you ever read about posts that focus on anti-smoking information from diverse social media platforms, even if you don't subscribe to them?	0.857	1.884
IN03	Have you ever been exposed to such health segments regarding anti-smoking on social media when you were not trying to find out?	0.836	1.727
IN04	Can you remember any anti-smoking information obtained unintentionally during the routine use of social media?	-	-
Perceived benefit (CR:1.000; AVE:1.000)			
PBE01	Anti-smoking will lower my chances of developing lung cancer or heart disease.	1.000	1.000
PBE02	Anti-smoking is beneficial to my health.	-	-
Perceived barriers (CR:0.875; AVE:0.778)			
PBA01	If I persuade others, I will feel embarrassed	-	-
PBA02	If I don't smoke, it is more difficult to socialize with others	0.842	1.467
PBA03	It is hard to persuade others as so many others around me are smoking	0.921	1.467
Perceived susceptibility (CR:0.836; AVE:0.631)			
PSU01	Do you worry that you will get lung cancer due to exposure to	0.751	1.609

	second-hand smoke?		
PSU02	Do you worry about the increased risk of developing heart disease due to exposure to second-hand smoke?	0.749	1.248
PSU03	Do you worry about the increased risk of respiratory illnesses due to second-hand smoke?	0.876	1.597
Perceived severity (CR:1.000; AVE:1.000)			
PSE01	How serious are tobacco-related diseases?	1.000	1.000
PSE02	How seriously does tobacco use cause respiratory problems?	-	-
PSE03	How seriously does tobacco use cause lung cancer?	-	-
Self-efficacy (CR:0.880; AVE:0.786)			
SE01	Are you confident that you will protect yourself from second-hand smoke?	0.870	1.490
SE02	Are you confident you will persuade your families or friends to quit smoking?	0.903	1.490
SE03	You feel agitated. Are you confident that you will not smoke	-	-
SE04	You see someone enjoy smoking. Are you confident that you will not smoke?	-	-
Smoking cessation behaviors (CR:1.000; AVE:1.000)			
B01	Have you ever attempted to persuade others to stop smoking?	1.000	1.000

Table 5.37. Discriminant validity tests result using the Fornell-Larcker criterion (among non-smokers)

	Behavior	IN	PBA	PBE	PSE	PSU	SE
Behavior[a]	1.000	-	-	-	-	-	-
IN[b]	0.412	0.861	-	-	-	-	-
PBA[c]	-0.266	-0.301	0.882	-	-	-	-
PBE[d]	0.385	0.219	-0.293	1.000	-	-	-
PSE[e]	0.225	0.143	-0.080	0.396	1.000	-	-
PSU[f]	0.135	0.091	-0.078	0.267	0.327	0.794	-
SE[g]	0.676	0.421	-0.444	0.519	0.268	0.155	0.887

[a] Behavior: persuade others to stop smoking

[b] IN: anti-smoking information scanning

[c] PBA: perceived barrier

[d] PBE: perceived benefit

[e] PSE: perceived severity

[f] PSU: perceived susceptibility

[g] SE: self-efficacy

Table 5.38. Discriminant validity tests result using the Heterotrait-Monotrait criterion (among non-smokers)

	Behavior	IN	PBA	PBE	PSE	PSU	SE
Behavior[a]	-	-	-	-	-	-	-
IN[b]	0.454	-	-	-	-	-	-
PBA[c]	0.031	0.388	-	-	-	-	-
PBE[d]	0.385	0.242	0.335	-	-	-	-
PSE[e]	0.225	0.159	0.089	0.396	-	-	-
PSU[f]	0.148	0.106	0.135	0.301	0.378	-	-
SE[g]	0.787	0.542	0.595	0.609	0.312	0.203	0.887

[a] Behavior: persuade others to stop smoking

[b] IN: anti-smoking information scanning

[c] PBA: perceived barrier

[d] PBE: perceived benefit

[e] PSE: perceived severity

[f] PSU: perceived susceptibility

[g] SE: self-efficacy

b) Structural model results

The proposed model explained 46.1% of the variance in non-smokers' anti-smoking behaviors, 4.8% of perceived benefits, 9.1% of perceived barriers, 2.1% of perceived severity, 8% of perceived susceptibility, and 17.7% of self-efficacy. And five of the ten proposed hypotheses were significant (for details, see Table 5.39). A significant correlation was found between anti-smoking information scanning and non-smokers' anti-smoking behaviors ($\beta = 0.281, p <$

.001).

Statistical tests demonstrated that anti-smoking information scanning was positively associated with non-smokers' perceived benefits ($\beta = 0.219, p < .001$), perceived severity ($\beta = 0.143, p < .01$), and self-efficacy ($\beta = 0.421, p < .001$). And anti-smoking information scanning negatively affected perceived barriers ($\beta = -0.301, p < .001$). However, no statistically significant correlation was observed between anti-smoking information scanning and perceived susceptibility. Only self-efficacy was found to be a significant mediator between anti-smoking information scanning and non-smokers' anti-smoking behaviors ($\beta = 0.664, p < .001$). None of the remaining path coefficients was significant. Hence, partial empirical support for the hypotheses was found in the present research (Figure 5.3)

Table 5.39. Results of hypotheses testing, path coefficients, t-statistics, f^2 value, and p-values (among non-smokers)

Hypothesis	Relationship	$\boldsymbol{\beta}$	T-value	P	f^2
H1a	IN and PBE	0.219	4.971	.000	0.051
H1e	IN and PBA	-0.301	7.077	.000	0.100
H1b	IN and PSE	0.143	3.139	.002	0.021
H1c	IN and PSU	0.091	1.759	.088	0.008
H1d	IN and SE	0.421	10.120	.000	0.215
H2a	PBE and B	0.038	0.793	.421	0.002
H2e	PBA and B	0.042	1.140	.262	0.002
H2b	PSE and B	0.032	0.852	.398	0.002
H2c	PSU and B	0.008	0.234	.813	0.000
H2d	SE and B	0.664	15.940	.000	0.515

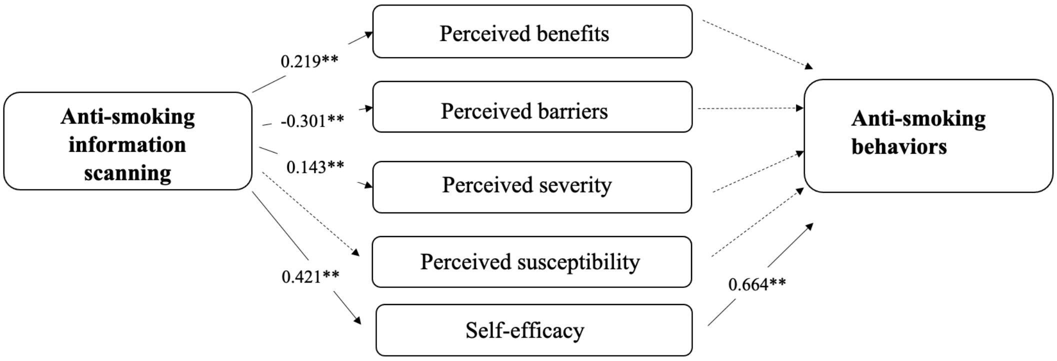


Figure 5.3. Path coefficients of the proposed relationships (among non-smokers)

Note: significance level: **P*< .05, ***P*< .01

5.3.7. Post-hoc analysis

1) Among smokers

a) Differences in mean values of seven constructs among socio-demographic groups of smokers

i. Gender and the mean values of constructs

Independent T-tests found significant differences in mean values of perceived barriers, perceived susceptibility, perceived severity, self-efficacy, and anti-smoking behaviors between females and males. As can be seen from the data in Table 5.40, the males reported significantly higher perceived barriers than the females, t (209.3) = 3.987, $p < .001$. And these results showed that the mean values of perceived severity, perceived susceptibility, self-efficacy and anti-smoking was significantly higher in females than males, t (312.2) = -2.375, $p < .05$, t (256.9) = -2.239, $p < .05$, t (295.5) = -3.931, $p < .001$, respectively. And there was no evidence that the mean scores of anti-smoking information scanning and perceived barriers varied between the two groups.

Table 5.40. The independent t-tests on the mean values of seven constructs between female and male smokers (N=466)

Variables	**Female** (N=128) Mean (±SD)	**Male** (N=338) Mean (±SD)	**T value**	***P***
Information scanning	4.16(±0.62)	4.21(±0.64)	-0.746	.456
Perceived benefits	4.20 (±0.63)	4.12(±0.76)	-0.946	.345
Perceived barriers	2.17(±0.80)	2.54 (±1.09)	3.987	.000
Perceived susceptibility	4.36 (±0.43)	4.24(±0.59)	-2.239	.026
Perceived severity	4.59 (±0.52)	4.47 (±0.59)	-2.375	.018
Self-efficacy	3.78(±0.73)	3.45(±0.95)	-3.931	.000
Anti-smoking behaviors	4.33 (±0.71)	4.19 (±0.72)	-1.817	.070

ii. Age and the mean values of constructs

The results obtained from the independent t-test analysis are presented in table 5.41. Obviously, the elder group (over 32 years) compared to younger group (18 to 31 years) reported significant higher mean values of anti-smoking information scanning, t (463.9) = -3.481, p < .001, perceived susceptibility, t (464) = -3.153, p < .01, perceived severity, t (464) = -2.451, p < .05, and self-efficacy, t (464) = -2.321, p < .05. However, the two groups did not significantly differ in mean values of remaining constructs.

Table 5.41. The independent t-tests on the mean values of seven constructs between younger and older smokers (N=466)

Variables	**Younger** (N=261) Mean (±SD)	**Elder** (N=205) Mean (±SD)	**T value**	***P***
Information scanning	4.09(±0.68)	4.28(±0.54)	-3.481	.000
Perceived benefits	4.16(±0.75)	4.12(±0.68)	0.706	.481
Perceived barriers	2.51(±1.05)	2.35(±0.99)	1.626	.105
Perceived susceptibility	4.21(±0.56)	4.37(±0.54)	-3.153	.002
Perceived severity	4.44(±0.58)	4.58(±0.57)	-2.451	.015

Self-efficacy	3.46(±0.91)	3.65(±0.89)	-2.321	.021
Anti-smoking behaviors	4.18(±0.75)	4.29(±0.68)	-1.674	.095

iii. Income and mean values of constructs

Notably, there were significant mean differences in seven constructs between the two income groups (as shown in Table 5.42). T-test showed that the level of perceived barriers was significantly higher among the participants with lower monthly income, t (464) = 4.070, p <.001. Conversely, the participants with higher monthly income also demonstrated higher mean values of anti-smoking information scanning, t (328.6) = -3.058, p < .01, perceived benefits, t (378.3) = -3.030, p < .01, perceived susceptibility, t (464) = -3.771, p < .001, perceived severity, t (464) = -3.062, p < .01, self-efficacy, t (464) = -4.469, p < .001 and anti-smoking behaviors, t (464) = -2.294, p < .05.

Table 5.42. The independent t-tests on the mean values of seven constructs between smokers with lower and higher income (N=466)

Variables	**Lower income** (N=180) Mean (±SD)	**Higher income** (N=286) Mean (±SD)	**T value**	***P***
Information scanning	4.06(±0.69)	4.25(±0.57)	-3.058	.002
Perceived benefits	4.20(±0.72)	4.22(±0.71)	-3.030	.003
Perceived barriers	2.68(±1.06)	2.29(±0.98)	4.070	.000
Perceived susceptibility	4.16 (±0.55)	4.35 (±0.55)	-3.771	.000
Perceived severity	4.40 (±0.57)	4.57 (±0.58)	-3.062	.002
Self-efficacy	3.31(±0.94)	3.69 (±0.86)	-4.469	.000
Anti-smoking behaviors	4.13(±0.77)	4.29 (±0.69)	-2.294	.022

b) Differences in mean values of seven constructs between smokers with higher and lower self-reported health literacy

In this regard, the independent t-test was employed to determine whether the health literacy of the respondents would lead to different mean values of seven constructs. The results, as shown in Table 5.43, indicate that level of health literacy was not significantly associated with smokers' anti-smoking behaviors. However, it was significantly related to the mean values of scanning information acquisition regarding anti-smoking, t (368.2) = -4.252, $p < .001$. Also, the respondents who reported higher health literacy also showed higher perceptions of health benefits, t (464) = -3.072, $p < .01$, susceptibility, t (364.9) = -4.005, $p < .001$, severity, t (379.4) = -3.413, $p < .01$ and self-efficacy, t (464) = -3.575, $p < .001$. Notably, the level of perceived barriers was significantly higher in participants with lower health literacy, t (464) = 2.940, $p < .01$.

Table 5.43. The independent t-tests on the mean values of seven constructs between smokers with higher and lower health literacy (N=466)

Variables	**Lower health literacy** (N=206) Mean (±SD)	**Higher health literacy** (N=260) Mean (±SD)	**T value**	***P***
Information scanning	4.03(±0.71)	4.28(±0.53)	-4.252	.000
Perceived benefits	4.03(±0.77)	4.23(±0.68)	-3.072	.002
Perceived barriers	2.60 (±1.02)	2.32(±1.03)	2.940	.003
Perceived susceptibility	4.16 (±0.63)	4.37 (±0.47)	-4.005	.000
Perceived severity	4.40 (±0.65)	4.58 (±0.50)	-3.413	.001
Self-efficacy	3.38(±0.93)	3.68 (±0.87)	-3.575	.000
Anti-smoking behaviors	4.17(±0.79)	4.28 (±0.66)	-1.722	.086

c) Differences in mean values of seven constructs across smoking characteristics groups

i. TTF and mean values of constructs

It can be seen in Table 5.44 that the participants who reported smoking the first cigarette within 30 minutes demonstrated higher mean values of perceived barriers, $t\ (253.6) = 3.078$, $p < .01$. No statistically significant difference in other constructs was observed between the two groups.

Table 5.44. The independent t-tests on the mean values of seven constructs between comparison groups regarding TTF (N=466)

Variables	**Within 30 minutes** (N=149) Mean (±SD)	**Over 30 minutes** (N=317) Mean (±SD)	**T value**	***P***
Information scanning	4.21(±0.62)	4.15(±0.63)	0.983	.326
Perceived benefits	4.09(±0.71)	4.17(±0.73)	-1.171	.242
Perceived barriers	2.67(±1.13)	2.33(±0.97)	3.078	.002
Perceived susceptibility	4.34(±0.45)	4.24(±0.60)	1.881	.061
Perceived severity	4.53(±0.55)	4.49(±0.59)	0.736	.462
Self-efficacy	3.45(±0.94)	3.59(±0.89)	-1.555	.121
Anti-smoking behaviors	4.26(±0.79)	4.22(±0.69)	.521	.603

ii. CPD and mean values of constructs

Overall, respondents who reported a lower number of cigarettes smoked per day (CPD) reported a significantly lower level of perceived barriers, $t\ (355.2) = -3.537$, $p < .001$, and a higher level of self-efficacy, $t\ (464) = 2.052$, $p < .05$. Similarly, the participants with lower CPD were more likely to take action, $t\ (464) = 2.094$, $p < .05$ (Table 5.45).

Table 5.45. The independent t-tests on the mean values of seven constructs between comparison groups regarding CPD (N=466)

Variables	**Less than 10** (N=279) Mean (±SD)	**More than 10**(N=187) Mean (±SD)	**T value**	***P***
Information scanning	4.13(±0.65)	4.24(±0.58)	-1.900	.058
Perceived benefits	4.16(±0.71)	4.12(±0.75)	0.507	.612
Perceived barriers	2.30(±0.95)	2.65(±1.11)	-3.537	.000
Perceived susceptibility	4.25(±0.57)	4.32(±0.54)	-1.411	.159
Perceived severity	4.52(±0.57)	4.48(±0.58)	0.803	.422
Self-efficacy	3.62(±0.89)	3.44(±0.93)	2.052	.041
Anti-smoking behaviors	4.29(±0.71)	4.14(±0.73)	2.094	.037

d) Differences in path coefficients: multigroup analysis results

Overall, the anti-smoking information scanning didn't affect females and males, the younger and older smokers, the smokers with higher and lower income, the smokers with higher and lower health literacy, and the smokers with higher and lower nicotine addiction differently (Table 5.46).

Table 5.46. Differences in the total effect of anti-smoking information scanning among smokers

	Total effect (β)	**Diff**	***P***
Gender			
Female	0.141**	0.011	.890
Male	0.152**		
Age			
Younger	0.169**	0.060	.294

Elder	0.109*		
Income			
<8000	0.158**	0.037	.540
>8001	0.121**		
Health literacy			
Lower	0.139**	0.011	.839
Higher	0.128**		
TTF			
Within 30 minutes	0.163**	0.010	.866
Over 30 minutes	0.152**		
CPD			
Less than 10	0.185**	0.099	.115
More than 10	0.087		

As mentioned above, perceived benefits, perceived barriers, perceived severity, and self-efficacy mediate the association between anti-smoking information scanning and anti-smoking information behaviors among smokers. Furthermore, the results obtained from PLS-MGA revealed that the proposed model explained 11.6 % of the variance in anti-smoking behaviors among females, whereas it was 16.5% for males. The R^2 for the anti-smoking behaviors in the younger group (16 to 31 years) was 0.145, whereas for the elder group was 0.148. For the lower income group (less than 8000 yuan per month), the model explained 17.8% of the variation in anti-smoking behaviors, whereas, for the higher income group (over 8000 yuan per month), it was 0.114. For the lower health literacy group (4 or below), the R^2 for the anti-smoking behaviors was 0.142, whereas for the higher health literacy group (equivalent to 5) was 0.147. The R^2 for the anti-smoking behaviors in the higher TTF group (smoke first cigarette within 30 minutes after waking up) was 0.227, whereas for the lower TTF group (smoke first cigarette over 30 minutes after waking up) was 0.124. For the lower CPD group (the number of cigarettes smoked per day: less than 10), the R^2 was 0.154, whereas for the higher CPD group (the number of cigarettes smoked per day: more than 10), the R^2 was 0.150.

The results of the multigroup analysis are displayed in Table 5.47, which is quite revealing in several ways. Firstly, what stands out is that no significant correlation was found between perceived barriers and anti-smoking behaviors in females, the younger and the elder group, the lower and higher health literacy group, the higher TTF group, and the lower CPD group. Secondly, anti-smoking information scanning did not significantly influence perceived severity in females, the higher health literacy group, the higher TTF group, and the higher CPD group. Thirdly, there has no significant association between anti-smoking information scanning and perceived benefits in the higher TTF group. Next, no significant correlation was found between self-efficacy and anti-smoking behaviors among females. Also, there is no evidence that perceived severity influences anti-smoking behaviors among the participants with lower monthly income. Regarding the differences in path coefficients, the results revealed that perceived susceptibility exerts a more decisive impact on anti-smoking behaviors in females than in males (difference=0.286, p <.05). None of the remaining differences were evident.

Table 5.47. Results of multigroup analysis across comparison groups among smokers

	H1a	H1e	H1b	H1c	H1d	H2a	H2e	H2b	H2c	H2d
Gender										
Female	0.269**	-0.268**	0.099	0.423**	0.357**	0.040	0.113	0.107	0.254**	0.120
Male	0.295**	-0.257**	0.228**	0.467**	0.362**	0.085	0.147*	0.183**	-0.032	0.382*
Diff	-0.026	-0.012	-0.129	-0.044	-0.004	-0.045	-0.034	-0.076	**0.286***	-0.262
P	.844	.884	.222	.703	.976	.673	.800	.485	**.037**	.058
Age										
Younger	0.325**	-0.243**	0.195**	0.483**	0.348**	0.036	0.060	0.140*	0.108	0.265**
Elder	0.249**	-0.261**	0.157**	0.370**	0.325**	0.135	0.172	0.186*	-0.065	0.354**
Diff	0.076	0.018	0.038	0.113	0.024	-0.099	-0.112	-0.046	0.173	-0.089
P	.506	.849	.715	.343	.801	.334	.358	.635	.159	.520
Income										
<8000	0.315**	-0.277**	0.218**	0.479**	0.317**	0.106	0.162*	0.138	0.040	0.378**
>8001	0.250**	-0.211**	0.155*	0.414**	0.339**	0.059	0.053	0.182**	0.052	0.208*
Diff	0.065	-0.067	0.064	0.065	-0.022	0.053	0.103	-0.044	-0.011	0.170
P	.489	.561	.563	.530	.814	.609	.391	.661	.917	.177
Health literacy										
lower	0.243**	-0.248**	0.208**	0.460**	0.355**	0.142	0.091	0.165*	0.000	0.263*
Higher	0.299**	-0.231**	0.119	0.391**	0.304**	0.007	0.152	0.158**	0.092	0.350**
Diff.	-0.056	-0.017	0.088	0.069	0.051	0.134	-0.061	0.006	-0.092	-0.087
P	.606	.861	.381	.477	.573	.182	.615	.952	.442	.507
TTF										
Within 30	0.192	-0.310**	0.160	0.375**	0.295**	-0.012	0.082	0.245*	0.062	0.434**

minutes										
Over 30 minutes	0.332**	-0.241**	0.211**	0.483**	0.377**	0.111	0.152*	0.153**	0.038	0.269**
Diff.	-0.139	-0.069	-0.051	-0.108	-0.082	-0.123	-0.070	0.093	0.023	0.165
P	.306	.475	.673	.396	.378	.254	.557	.350	.848	.220
CPD										
Less than 10	0.307**	-0.298**	0.226**	0.423**	0.409**	0.092	0.076	0.162*	0.115	0.231**
More than 10	0.260**	-0.260**	0.158	0.500**	0.283**	0.062	0.212*	0.174*	-0.046	0.427**
Diff.	0.048	-0.038	0.068	-0.077	0.126	0.030	-0.136	-0.012	0.160	-0.196
P	.694	.702	.545	.455	.173	.772	.288	.902	.243	.162

2) Among non-smokers

a) Differences in mean values of seven constructs among socio-demographic groups of non-smokers

i. Gender and mean values of constructs

Overall, the mean values of the seven constructs did not vary between the males and females (see details in Table 5.48).

Table 5.48. The independent t-tests on the mean values of seven constructs between female and male non-smokers (N=455)

Variables	**Female** (N=329) Mean (±SD)	**Male** (N=126) Mean (±SD)	**T value**	***P***
Information scanning	3.82 (±0.90)	3.88(±0.88)	0.696	.486
Perceived benefits	4.13(±0.84)	4.26(±0.86)	1.450	.148
Perceived barriers	2.78(±1.10)	2.86(±1.15)	0.689	.491

Perceived susceptibility	4.31(±0.57)	4.18(±0.79)	-1.685	.094
Perceived severity	4.29(±0.78)	4.39(±0.70)	1.184	.237
Self-efficacy	3.65(±0.85)	3.68(±0.84)	0.322	.748
Anti-smoking behaviors	3.95(±0.93)	3.83(±0.91)	-1.175	.248

ii. Age and mean values of constructs

As presented in Table 5.49, firstly, the level of anti-smoking information scanning was significantly associated with the age of the participants, that the younger (18 to 28 years) reported lower mean values than the elder (over 29 years), t (449.3) = -3.972, p < .001. Secondly, the mean values of respondents' perceptions also were significantly different between the two groups, including perceived benefits, t (453) = -2.102, p < .05, and self-efficacy, t (453) = -2.390, p < .05. No evidence was found for remaining differences in constructs regarding health perceptions between the younger and the elder. But the significant difference in anti-smoking behaviors between the two groups remained, that the elder reported higher mean scores than the younger, t (452.8) = -2.787, p < .001.

Table 5.49. The independent t-tests on the mean values of seven constructs between younger and older non-smokers (N=455)

Variables	**Younger** (N=247) Mean (±SD)	**Elder** (N=208) Mean (±SD)	**T value**	***P***
Information scanning	3.68(±0.91)	4.01(±0.84)	-3.972	.000
Perceived benefits	4.09(±0.88)	4.26(±0.79)	-2.102	.036
Perceived barriers	2.84(±1.09)	2.74(±1.14)	0.939	.348
Perceived susceptibility	4.30(±0.60)	4.24(±0.69)	0.996	.320
Perceived severity	4.31(±0.77)	4.34(±0.74)	-0.404	.687
Self-efficacy	3.57(±0.87)	3.75(±0.81)	-2.390	.017

Anti-smoking behaviors	3.81(±0.98)	4.04(±0.84)	-2.787	.006

iii. Income and mean values of constructs

As shown in Table 5.50, the results revealed that different monthly incomes would lead to different levels of health perceptions, as well as anti-smoking information scanning and anti-smoking behaviors. Furthermore, the participants with higher monthly income were more likely to be exposed to anti-smoking information, t (312.8) = -3.995, $p < .001$. Similarly, this group also reported significantly higher mean values of anti-smoking behaviors, t (375.8) = -4.552, $p < .001$. Regarding health perceptions, the level of perceived benefits, perceived severity and self-efficacy was higher among the participants with higher monthly income, t (389.6) = -2.719, $p < .01$, t (372.2) = -2.139, $p < .05$, t (393.8) = -5.773, $p < .001$, respectively. Conversely, the participants who reported lower monthly income showed significantly higher mean values of perceived barriers, t (453) = 2.868, $p < .01$.

Table 5.50. The independent t-tests on the mean values of seven constructs between non-smokers with lower and higher income (N=455)

Variables	**Lower income** (N=305) Mean (±SD)	**Higher income** (N=150) Mean (±SD)	**T value**	***P***
Information scanning	3.72(±0.89)	4.06(±0.85)	-3.995	.000
Perceived benefits	4.10(±0.91)	4.31(±0.67)	-2.719	.007
Perceived barriers	2.90(±1.10)	2.59(±1.11)	2.868	.004
Perceived susceptibility	4.27(±0.81)	4.42(±0.63)	1.326	.186
Perceived severity	4.30(±0.59)	4.21(±0.73)	-2.139	.033
Self-efficacy	3.51(±0.90)	3.94(±0.64)	-5.773	.000
Anti-smoking behaviors	3.79(±0.98)	4.17(±0.75)	-4.552	.000

b) Differences in mean values of seven constructs among non-smokers with higher and lower health literacy

The differences between the two groups are highlighted in Table 5.51. It is apparent that there was a significant difference in the mean values of anti-smoking information scanning, t (415.4) = -7.649, $p < .001$, perceived benefits, t (453) = -4.249, $p < .001$, perceived severity, t (453) = -2.886, $p < .01$, perceived susceptibility, t (453) = -2.389, $p < .05$, self-efficacy, t (453) = -5.706, $p < .001$ and anti-smoking behaviors, t (438.3) = -5.605, $p < .001$, that the respondents with higher health literacy also reported higher level of these six constructs. In contrast, the level of perceived barriers was higher among respondents with lower health literacy compared to those with higher health literacy, t (453) = 3.213, $p < .01$.

Table 5.51. The independent t-test on the mean values of seven constructs between non-smokers with higher and lower health literacy (N=455)

Variables	**Lower health literacy** (N=228) Mean (±SD)	**Higher health literacy** (N=227) Mean (±SD)	**T value**	***P***
Information scanning	3.53(±0.96)	4.13(±0.70)	-7.649	.000
Perceived benefits	4.00 (±0.85)	4.33 (±0.81)	-4.249	.000
Perceived barriers	2.97(±1.08)	2.63(±1.13)	3.213	.001
Perceived susceptibility	4.20(±0.64)	4.34(±0.64)	-2.389	.017
Perceived severity	4.22(±0.79)	4.42(±0.72)	-2.286	.004
Self-efficacy	3.43(±0.86)	3.87(±0.79)	-5.706	.000
Anti-smoking behaviors	3.68(±0.98)	4.15(±0.81)	-5.605	.000

c) Differences in path coefficients: multigroup analysis results

The results mentioned above indicated that the anti-smoking information is associated with anti-smoking behaviors only through the self-efficacy of non-smokers. Overall, the proposed model explained 44.9% of the variation in the anti-smoking behaviors in the females, whereas 52% in the males. For the younger group (18-28 years), the R^2 for the anti-smoking behaviors was 0.461, whereas it was 0.466 in the elder group (over 29 years). For the lower monthly income group (less than 8000 yuan per month), the model explained 47.2% of the variance in the anti-smoking behaviors, whereas 34.8% in the higher monthly income group (more than 8000 yuan per month). The R^2 for the anti-smoking behaviors in the lower health literacy group (4 or below) was 0.470, whereas it was 0.396 for the higher health literacy group (equivalent to 5). As shown in Table 5.52, no statistically significant differences in the total effect of anti-smoking information scanning were found in all these population groups.

The results revealed that the anti-smoking information scanning affects males and females differently in perceived barriers (difference=0.219, p < .001). From Table 5.53, it can be seen that there was a statistically significant association between anti-smoking information scanning and perceived susceptibility in females ($\beta = 0.173, p < .001$) and in the lower monthly income group ($\beta = 0.165, p < .001$). However, no significant correlation was observed between anti-smoking information scanning and perceived severity in the elder group, the higher monthly income group, and the lower health literacy group. None of the remaining differences in other relationships remained.

Table 5.52. Differences in the total effect of anti-smoking information scanning among non-smokers

	Total effect (β)	**Diff.**	***P***

Gender			
Female	0.274**	0.023	.709
Male	0.307**		
Age			
Younger	0.248**	0.064	.321
Elder	0.312*		
Income			
<8000	0.270**	0.027	.688
>8001	0.243**		
Health literacy			
Lower	0.254**	0.023	.705
Higher	0.231**		

Table 5.53. Results of multigroup analysis across comparison groups among non-smokers

	H1a	**H1e**	**H1b**	H1c	**H1d**	H2a	H2e	H2b	H2c	**H2d**
Gender										
Female	0.177**	-0.243**	0.110*	0.173**	0.422**	0.042	0.056	0.032	-0.024	0.665**
Male	0.329**	-0.462**	0.230**	-0.051	0.419**	0.042	0.006	0.070	0.072	0.677**
Diff.	-0.153	0.219	-0.120	0.223	0.002	0.000	0.049	-0.037	-0.096	-0.012
P	.073	.000	.220	.119	.973	.999	.557	.667	.251	.882
Age										
Younger	0.224**	-0.248**	0.201**	0.119	0.355**	0.033	-0.009	0.069	0.055	0.355**
Elder	0.187**	-0.367**	0.065	0.140	0.488**	0.097	0.044	-0.047	-0.046	0.716**

Diff.	0.037	0.120	0.136	-0.021	-0.133	-0.011	-0.106	0.116	0.101	-0.102
P	.668	.145	.134	.692	.091	.900	.169	.141	.215	.231
Income										
<8000	0.201**	-0.269**	0.122*	0.165**	0.398**	0.009	0.040	0.016	0.038	0.618**
>8001	0.214*	-0.330**	0.154	-0.063	0.424**	0.103	0.068	0.034	-0.060	0.553**
Diff.	-0.013	0.062	-0.031	0.228	-0.026	-0.094	-0.028	-0.018	0.098	0.128
P	.885	.479	.750	.158	.758	.358	.743	.829	.351	.143
Health literacy										
lower	0.131*	-0.282**	0.028	0.109	0.373**	-0.005	0.019	-0.014	0.006	0.697**
Higher	0.228**	-0.272**	0.234**	-0.015	0.365**	0.067	0.063	0.103	0.001	0.573**
Diff.	-0.097	-0.011	-0.207	0.124	0.008	-0.072	-0.044	-0.117	0.005	0.124
P	.284	.893	.030	.295	.922	.450	.565	.139	.947	.146

CHAPTER 6

Discussion

6.1. Effectiveness evaluation of anti-smoking information scanning via social media

6.1.1. Total effect: the relationship between anti-smoking information scanning via social media and anti-smoking behaviors

As mentioned in the literature review, the association between online health information acquisition and favorable health outcomes has been intensively validated (e.g., Bowles et al., 2020; Liu & Jiang et al., 2021). Considering all of this evidence, it seems to outline a major role of social media platforms in an individual's smoking-related decisions and public smoking education (Lazard et al., 2021; Meacham et al., 2021). In reviewing the literature, very little was found on the total effect of anti-smoking information scanning on social media platforms in China. Thus, the central research question in this dissertation sought to determine how unintentional anti-smoking information acquisition via social media influences actual anti-smoking behaviors of Chinese users in daily life.

In this respect, based on the theory of planned behavior model (TPB) and the health belief model (HBM), the most prominent finding to emerge from these analyses is that anti-smoking information scanning is positively associated with anti-smoking behaviors of Chinese social media users by influencing their health perceptions and psychological factors, not only among smokers but among the non-smokers as well. This finding also accords with the work of previous studies linking communication behaviors and health behaviors in the domain of health communication (e.g., Bigsby & Hovick, 2018; Strømme et al., 2018). On the one hand, despite the relationship between online health information acquisition and health outcomes has attracted conflicting interpretations as above mentioned in the research literature (see details in Chapter 2, 2.3.5), the present dissertation provides strong evidence that desirable anti-smoking behaviors have occurred due to Chinese users' routine exposure to a wide range of anti-smoking-related topics delivered by multiple information sources in rich and diverse forms on different channels, which also owe much to popularity, various functionalities and heterogenous nature of social media platforms, including interactive characteristics and informational features (as discussed in Chapter 2.1.1). On the other hand, the current empirical research has important practical implications for creating a supportive and persuasive atmosphere on social media platforms to increase public knowledge and guide public attention, thereby educating and encouraging users to engage in anti-smoking behaviors (Lazard et al., 2020; Yoo et al., 2016).

6.1.2. Direct effect: the relationship between anti-smoking information scanning via social media and the participants' attitudes and perceptions

In view of all that has been mentioned so far, a large and growing body of literature has explained the complexity of health behavioral changes by using the theory of planned behavior model or the health belief model, which has proposed different determinants reflecting a person's perceptions and psychological characteristics, such as Wong et al. (2021) and Hamilton et al. (2020). Therefore, the second and third studies in this dissertation aimed to assess the direct impact of anti-smoking information scanning via social media on health perceptions and attitudes of social media users, clarifying the underlying behavioral mechanisms. In particular, both studies respectively explored the determinants associated with anti-smoking information scanning on social media among current smokers and non-smokers.

1) Among smokers

Based on the health belief model and the theory of planned behavior model, this dissertation produced results that corroborate the findings of a great deal of the previous work, which found that unintentional exposure to anti-smoking information on social media platforms is closely correlated to smokers' health perceptions towards tobacco use, including behavioral attitudes, subjective norms, self-efficacy, perceived benefits, perceived barriers, perceived severity and perceived susceptibility (Cho et al., 2021; Upadhyay et al., 2019; Yanti et al., 2020). These findings may be taken to indicate that passive anti-smoking information acquisition not only can make smokers more knowledgeable about cumulative health hazards of tobacco use, as well as positive consequences and effective ways of smoking cessation, increase their risk beliefs by providing informational support but also can enforce their sense of community or belonging by offering emotional support (Chou et al., 2018; Talyor et al., 2017; Yu et al., 2015). Additionally, these results match those observed in the first study about content analysis of anti-smoking-themed posts on social media platforms in China, which found that the disseminated messages regarding the hazards of tobacco use, the smoking ban, and smoking cessation have been more prevalent on social media platforms (see details in Chapter 3). In other words, it confirms that the current smokers have benefitted from the continuous stream of anti-smoking messages on social media, particularly from the posts concerning these three themes, influencing their thinking and feeling about tobacco use as mentioned above.

2) Among non-smokers

Similarly, this dissertation found that the perceived benefits, perceived barriers, perceived severity, behavioral attitudes, subjective norms, and self-efficacy of non-smokers were affected by incidental exposure to anti-smoking messages on social media. These results are in accord with recent studies indicating the positive impact of anti-smoking campaigns on non-smokers' risk perceptions and favorable beliefs (Choi & Jeong, 2021; Shadel et al., 2019).

However, one interesting finding is that non-smokers' perceived susceptibility was not promoted. These differences can be partly explained by a relatively small volume of anti-smoking messages on social media regarding multiple health problems caused by second-hand smoking, which shows in the first study that these relevant posts are the second fewest during the study time frame. Hence, the participants were informed of the seriousness of tobacco-related diseases, and they have become more confident and capable of protecting themselves during routine exposure. However, their awareness of the risk caused by second-hand smoke still needs to be enhanced. In general, the findings reported here might further indicate that health practitioners have to pay more attention to clarifying the negative externalities imposed by smokers on non-smokers from all aspects through multiple digital platforms, such as environmental, economic, health, and societal externalities.

Another interesting finding is that a significant correlation was found between anti-smoking information scanning and subjective norms among non-smokers. These results differ from some published studies (Li, Y., 2017; Rhodes et al., 2008), but they are consistent with the findings of other studies (e.g., Kim et al., 2018). In this regard, this significant linkage maybe since the voices of content providers on social media has become the same or even more persuasive than users' social contacts in their proximate world, given that disseminated messages via digital media are diverse, controversial, and attractive (Wang, Y et al., 2021). Notably, as a complex picture of an individual's perceptions of their social referents' expectations or approval, these findings suggest that a broader conceptualization of non-smokers' social norm perceptions needs to be taken into account to investigate the effect of anti-smoking campaigns in further research, particularly under the Chinese social context of anti-smoking, not only considering subjective norms but also measuring descriptive and injective norms (Dono et al., 2020; Lee & Paek, 2013). Meanwhile, one of the intriguing questions emerging from this finding is which appeal types of anti-smoking messages can contribute to greater subjective norms among non-smokers, such as health-related threats or social threats and cognitive or affective appeals (e.g., Halkjelsvik & Rise, 2015).

6.1.3. Significant mediators between anti-smoking information scanning and anti-smoking behaviors

Notably, previous studies evaluating the impact of online health information acquisition observed inconsistent results on which principal determining factors between anti-smoking information scanning and anti-smoking behaviors and how these mediators vary among different population groups. Psychological speaking, the second and the third study measuring the various domains of an individual's perceptions concerning anti-smoking based on the health belief model and the theory of planned behavior model, respectively, revealed that smokers' perceived severity, self-efficacy, and behavioral attitudes are positively associated with the uptake of anti-smoking behaviors. In contrast, their perceptions of obstacles to anti-smoking have a negative influence on ultimate behaviors. However, only greater self-efficacy is closely associated with the increased likelihood of non-smokers' anti-smoking behaviors.

Comparison of the findings reported here with those of previous studies identified an individual's greater health perceptions and attitudes as significant predictors to motivate desirable health behaviors, but these preconditions may vary across different populations and social contexts, also depending on different health issues concerned (Anuar et al., 2020; Alton et al., 2018; Kaufman et al., 2018; Zhao et al., 2019). From this perspective, despite HBM and TPB taking different approaches to assess health cognitions and demonstrating the process of behavioral changes, these two studies provided empirical evidence of their applicability to the Chinese context in the case of tobacco education.

It noted that the current dissertation had been discussed from the viewpoints of communication rather than psychology, focusing specifically on whether and how scanning information acquisition related to anti-smoking influences an individual's anti-smoking behaviors. Therefore, these perceptions, which were proved as significant mediators, were leveraged to confirm which aspects must be strengthened by conveying an anti-smoking message across social media platforms. In other words, the combination of findings will help health and communication practitioners to design more persuasive anti-smoking campaign messages for future efforts, which have a potential impact not only on health outcomes but also on anti-smoking message reach (Jiang & Beaudoin, 2016). In this regard, for example, the negative health consequences of tobacco use must be stressed to smokers, especially male smokers, as perceived severity was determined as a critical predictor of behavior characteristics in these groups. Similarly, empirical research also suggests the importance of perceived susceptibility among smokers, especially among female smokers. Hence, campaign designers have to focus more on clarifying the incidence of tobacco-related diseases in these groups. In fact, in accordance with the present observations, a great deal of the previous research also explains which constituent part of disseminated messages should be underlined by theoretically examining the health behavior models, such as Arif et al. (2022), Jiang et al. (2021) and Zhang et al. (2017).

Contrary to expectation, the second study found that subjective norms don’t have a positive influence on anti-smoking behaviors among non-smokers. And this weak association of subjective norms and anti-smoking behaviors of all the participants is somewhat surprising given the fact that previous research shows the more significant impact of social norms on health behaviors than personal behavioral attitudes in a collectivistic society, such as China (Hosking et al., 2009; Hassan et al., 2016; Li, L., & Li, J., 2020). And another exciting finding is that self-efficacy is the only psychological factor motivating actual anti-smoking behaviors of a non-smoker. This result is generally in line with previous studies documenting self-efficacy's prominent roles in anti-smoking (Cousson-Gélie et al., 2018; Zvolensky et al., 2018). In fact, this finding was unexpected due to the conclusions derived from previous cross-culture research regarding the mediation effect of individualism and collectivism on attitude-behavior relationships. Conceptually, individualists value personal performance, control, and achievements. At the same time, collectivists (e.g., Chinese) are more sensitive to social contexts and relationships, thereby resulting in differential impact of self-related concepts (e.g., self-efficacy) and social factors (e.g., subjective norms) on behavioral changes (Cheng et al., 2020; Markus & Kitayama, 1991). As such, in a collectivistic national culture (e.g., China), people are more likely to follow social norms and shift their behaviors depending on the majority opinions or the thoughts of others. In individualistic cultures, self-efficacy has been recognized as a stronger predictor of decision-making (Cho & Lee, 2015). In the current dissertation, the more critical roles of self-efficacy rather than social norms on participants' anti-smoking behaviors raise the possibility of a rise in individualism in contemporary China over time (Cai et al., 2018; Ogihara, 2020). And these findings challenge the notion that the Chinese are more attuned to consensus information and have important implications for emphasizing a function of culture in health education and adjusting content strategies to the changing society.

6.2. The roles of individual and social determinants in the relationship between anti-smoking information scanning and anti-smoking behaviors

After identifying the total effect of anti-smoking information scanning via social media on anti-smoking behaviors among smokers and non-smokers, as well as determining its direct impact on an individual's perceptions and attitudes and significant mediators between the proposed relationships, several essential questions remain about effect modification of these relationships by social and individual determinants, such as gender, age, income, education and smoking characteristics. In other words, some prior studies have shown the beneficial effects of digital anti-smoking messages. Still, a much-debated question is whether and how these relationships vary among different subgroups.

According to the above reasons, as a strong relationship between social determinants and communication outcomes has been confirmed in the literature, such as Jacobs et al. (2017) and Koiranen et al. (2020), multiple linear regression analysis was conducted in the second and third studies, respectively, to determine whether social and individual determinants of the participants were related to communication disparities in the exposure of anti-smoking information during their routine use of social media platforms. Furthermore, multigroup analysis was utilized in the second study to quantitatively describe the differences in the six relationships proposed based on the theory of planned behavior model between smokers and non-smokers and also identify the differences in the total effect of anti-smoking information scanning between gender, age, income, and education groups. Similarly, the differences in the ten relationships proposed based on the health belief model were evaluated in the third study using multigroup analysis.

Taken together, all these analyses mentioned above were further designed to determine the extent to which social and individual determinants mediate the relationship between anti-smoking information scanning via social media, users' perceptions, and ultimate anti-smoking behaviors. It intends to ascertain communication disparities in passive anti-smoking information acquisition via social media, provide theoretical support for digital anti-smoking message segmentation, develop a better understanding of the link between communication disparities and health disparities and discuss the roles of social media platforms in reducing or increasing these disparities.

6.2.1. Differences in anti-smoking information scanning via social media among population subgroups

According to the results of multiple linear regression analyses in the second study, monthly income and age were related to anti-smoking information scanning among smokers and non-smokers. The results of the third study show that age, education level, self-reported health status, and health literacy have an influence on anti-smoking information scanning among smokers. More importantly, although no evidence was found for a linear association between smokers' monthly income and their anti-smoking information scanning behaviors, the Pearson's correlation analysis results indicate that monthly income positively correlated to anti-smoking information scanning via social media among smokers. Additionally, non-smokers' monthly income, health status, and health literacy were identified as key determinants of their anti-smoking information scanning. Also, based on Pearson's correlation analysis, there was a positive correlation between non-smokers' age and their scanning information acquisition. To sum up, income, age, health status, and health literacy were found to cause differences in unintentional anti-smoking information acquisition via social media among smokers and non-smokers. Another important finding was that education level was determined as a critical predictor specific for smokers' anti-smoking information scanning.

These results must be interpreted with caution because anti-smoking information scanning was measured using self-reported recall. There is a potential for an individual's recall bias (Neff et al., 2016; Prior, 2009). In addition, the results showed that the coefficients of determination (R^2) were small in five regression models. Notably, the results of the one-way ANOVA test on the frequency of social media use among socio-demographic groups revealed that except in education groups of smokers, none of the remaining differences was significant. It is possible that such disparities in unintentional anti-smoking information acquisition were not completely caused by social media use intensity. Therefore, this observation may support the hypothesis that anti-smoking information scanning via social media was affected not only by social and individual determinants but also by a host of other variables, such as prior knowledge, social surroundings, and even memory (van Meurs et al., 2022).

In general, these results agree with the findings of other studies, which indicate that an individual with higher monthly income, health literacy, health status, and educational attainment also reported relatively more increased use of online information (Alvarez-Galvez et al., 2020; Hruska & Maresova, 2020; Kontos et al.; 2014). It noted that communication disparities in the exposure of anti-smoking information were not caused by the separation between those who have access to social media platforms and those who don't, as all the participants recruited in the current dissertation are social media users. In fact, this disparity might be related to a second-level digital divide (usage gap), referring to individual's lifestyle, frequency of use, differentiated uses of social media platforms, and even the anti-smoking information environment created by communication and health practitioners in China (Hong et al., 2017; Van Deursen & Helsper, 2015). On the other side, the findings reported here are somewhat surprising that previous studies have identified more differences by social and individual determinants in online health information seeking rather than information scanning because a search for health information via the internet requires greater technological skills while a minimal effort is made to scanning information acquisition (Correa, 2016; Jacob et al., 2017; Jiang et al.,2021). These differences can be explained in part by the filter-bubble hypothesis that an individual is possibly more likely to engage with such homogenous information because web-based platforms utilize recommender systems to offer personalized content according to users' seeking behaviors or personal habits (Grossetti et al., 2020; Majmundar et al.,2019). As the previous studies have noted that health information seeking is performed by people with higher income, health status, and education level (e.g., Bahandari et al., 2020; Wang et al., 2021), it is probable therefore that disparities in anti-smoking information scanning were related to users' information seeking or individual interests regarding tobacco use. Additionally, we might think of the more crowded information environment for the participants reporting higher anti-smoking information scanning that they are more likely to be exposed to pro-smoking messages on social media platforms as well (Bekalu et al., 2022).

Furthermore, in contrast to earlier findings, these studies have been unable to demonstrate that women and younger age groups have a higher likelihood of accessing online anti-smoking information (Alvarez-Galvez et al., 2020; Chukwuere & Chukwuere, 2017; Estacio et al., 2019; Jaafar et al., 2019). On the one hand, these findings revealed that anti-smoking information scanning via social media increases with the age of smokers and non-smokers. It is possible that these results were limited by the lack of participants sixty-three years old and above, so the generational shift didn't occur (Alvarez-Galvez et al., 2020; Kontos et al., 2014). And this result may partly be explained by the increased concerns about well-being among older Chinese (Xiong et al.,2021). On the other hand, the results regarding gender distinction are in keeping with previous studies, which found no differences in passive participation levels between males and females during the routine use of social media (Zhang, Y et al.,2021). Despite this, these findings are somewhat unexpected, considering the fact that younger generations and females prefer relying on social media platforms not only for searching for health information but also for passively obtaining it (Jacobs et al., 2015; Lloyd et al., 2018; Nelissen et al., 2015). As mentioned above, the younger generations are more receptive to smoking education harnessing social media, and females tend to use social media platforms for health-related purposes. Therefore, social media-based tobacco education needs to make great efforts to attract these two at-risk groups (Zhang et al., 2022).

6.2.2. Differences in the direct impact of anti-smoking information scanning on health attitudes and perceptions among population subgroups

With respect to questions about the existing differences in the relationship of passive anti-smoking acquisition on social media and users' health attitudes and perceptions, the third study, whose theoretical framework was established based on the health belief model and the structural influence model of communication, found that most of the differences in path coefficients in gender groups, age groups, income groups, health literacy groups, TTF groups, and CPD groups, were not significant. These findings of the third study don't support the previous research, such as Bekalu et al. (2022) and Bigsby and Hovick (2018), but they are in line with others, such as Colston et al. (2022). Here, in this regard, a note of caution is due here since the multigroup analysis using partial least squares modeling was conducted by dividing the participants into two subgroups according to their gender, age, health literacy, TTF, and CPD. To ensure a similar sample size for each group, education level and self-reported health status were not taken into account, and there have only two subgroups in each division. Therefore, these findings may be somewhat limited.

But, regardless of that, consistent with the literature, most non-significant differences indicated that more and more acceptable and usable anti-smoking messages delivered through various social media platforms not only show much promise in influencing public health perceptions but also effectively reduce disparities in tobacco-related perceptions among multiple audiences (Colston et al., 2022; Liao, 2019; Petkovic et al., 2021). These findings also provide some support for those observed in earlier studies, which demonstrated that health campaigns harnessing social media offer opportunities for facilitating knowledge dissemination to reach a broader audience, especially disadvantaged populations, by providing a wealth of understandable, attractive, and personalized information given the continuous advancement in technology (Al-Dmour et al., 2020; Chen & Wang, 2021; Yu et al.,2015). Additionally, it is worth noting that individuals who acquire health information by scanning instead of seeking it could be less critical. They are more likely to believe all the information available without further distinguishment and confirmation, which may explain why most of the proposed relationship between anti-smoking information scanning and user perceptions was not mediated by gender, age, income, health literacy, and smoking characteristics (TTF and CPD) (Liu & Jiang, 2021).

In the third study, only a small part of differences in the relationship between anti-smoking information scanning and health cognitions was observed, which also accords with the previous studies based on the structural influence model of communication (Bekalu et al., 2022; Bekalu & Eggermont, 2014; Viswanath et al., 2007). Notably, it was surprising that the impact of anti-smoking information scanning on an individual’s perceived barriers, perceived susceptibility, and perceived severity differed significantly between gender groups. First of all, in contrast to earlier studies, a critical finding in the current study is that there is no positive relationship between anti-smoking information scanning and female smokers’ perceived severity. The opposite is true among male smokers. It is difficult to explain this result, but it may be related to Chinese culture. Social contexts of tobacco use that a majority of anti-smoking messages disseminated on different channels in China have mainly been targeted at male smokers rather than female smokers because smoking by females has been regarded as taboo but has been viewed as a common way for males in the traditional Chinese view (Wu et al., 2019; Yang et al., 2021). This nonsignificant association is in agreement with those obtained by the first study in the current dissertation (Content analysis of anti-smoking-themed posts on social media platforms in China, see details in Chapter 3), which showed that lots of anti-smoking campaigns were designed by a male perspective, emphasizing harmful effects of tobacco use on men's health and pregnant women's health. Still, few anti-smoking posts specifically focused on unique or common smoking-related health risks to female smokers, such as cervical cancer and mental health problems (Haghani et al., 2020; Smit et al., 2019). In the same vein, the existing anti-smoking posts have stressed the health threat posed by second-hand smoke for females, especially for female non-smokers, including their families and children, because people acquiesced that females are passive smokers in China. These facts may also explain a significant relationship between anti-smoking information scanning and female non-smokers' perceived susceptibility but not in male non-smokers.

Another unexpected finding is that anti-smoking information scanning exerts a more decisive influence on perceived barriers of male non-smokers than female non-smokers. As noted earlier, these differences may partly be explained by the fact that anti-smoking campaigns have more concerned with the critical social functions and cultural meanings of smoking and cigarettes performed in a man's world, such as smoking symbolizing male power, career success, and better social interactions. Hence, from this perspective, the disseminated anti-smoking posts proposed corresponding solutions that are more practical for male non-smokers rather than females, making them more capable of coping with barriers (Yang & Hendley, 2018). With the increased female smoking prevalence in China, the findings reported here suggest that more efforts are needed to increase female perceptions regarding the dangers of both active smoking and tobacco initiatives in an anti-smoking message since women have become the at-risk group and neglected audiences of tobacco education and the use of social media platforms by this group is disproportionately high (Chen et al., 2015; Sansone et al., 2015; Xiao & Wang, 2019). It can thus be suggested that the gender specificity and the societal context of women's tobacco use have to be considered more thoroughly in further research and future tobacco control (Baheiraei et al., 2016; Amos et al., 2012; Solomon, 2020). Also, these valuable results might indicate that not only an individual's perceptions regarding tobacco use but also the design of anti-smoking campaigns have been conditioned by cultural factors and stereotypes regarding smoking behaviors in Chinese society. Despite numerous studies have attempted to explain the social disparities in smoking, such as Tan and Bigman (2020) and Marbin and Gribben (2019), the results presented above raise intriguing questions about whether differences in anti-smoking behaviors, even in well-being have been caused by health practitioners' ongoing concentration on a specific group – current male smokers in China during the public smoking education.

Additionally, the results of the third study found that the perceptions of the seriousness of tobacco-related diseased were not affected by incidental exposure to anti-smoking information on social media platforms among smokers with higher nicotine addiction, including those who smoke more than ten cigarettes per day (higher CPD group) and who commonly smoke their first cigarette in 30 minutes after waking (higher TTF group). These nonsignificant associations may partly be explained by the disagreement on the effectiveness of anti-smoking messages containing different types of appeals to smokers' attitudes or behaviors that attempt to describe the negative consequence of tobacco use or the vulnerability of the audience, including fear appeal, emotional appeal and social appeal (Nicolini & Cassia, 2021; Shen & Dillard, 2014). The findings presented here suggest that anti-smoking messages have been perceived differently between smokers and non-smokers and between lower-addicted and higher-addicted smokers. Hence, more attention needs to be paid to personalizing digital anti-smoking messages, which can be more persuasive to those addicted smokers and, more importantly, won't provoke their defiance of common sense (Burgess et al., 2012; McCool et al., 2013).

Similarly, one unanticipated finding was that unintentional anti-smoking information acquisition can't contribute to greater perceived severity among the elder non-smokers (over 29 years) and those with higher monthly income (over 8000 yuan a month) or with lower health literacy. Meanwhile, there has the opposite effect on their control groups. As noted above, a possible explanation for these results may be the relative lack of anti-smoking messages regarding the negative externalities of smoking on social media platforms. Furthermore, an implication of these differences is the importance of greater consideration of the complexity of non-smokers in a tobacco control program. Mainly, anti-smoking posts may be treated as unrelated to their conditions among non-smokers. They have even become indifferent to the continuously increased number of anti-smoking posts with similar content, resulting in a higher risk for smoking initiation. As a result, despite the association between socioeconomic status (e.g., education and income) and tobacco initiation varied greatly across different regions in China, particular efforts should be given to maintaining the favorable perceptions of non-smokers, especially those who are vulnerable to tobacco initiation (Wang et al., 2018; Wu et al., 2019; Zhang et al., 2022).

Ample studies have demonstrated that more and more individuals reported being tired of repeated exposure to anti-smoking messages through diverse channels, and severe content homogeneity has caused anti-smoking message fatigue (Ibrahim, 2021; So & Popova, 2018). This also provides some explanation as to both significant and nonsignificant differences in the relationship between anti-smoking information scanning and an individual's health perceptions regarding anti-smoking among population groups. In other words, anti-smoking messages have become too familiar for social media users to stimulate improvements in their perceptions. Meanwhile, a ceiling effect has begun appearing that the tobacco-related perceptions of social media users could already be high (Bekalu et al., 2022; Maloney et al., 2016). Hence, the anti-smoking message novelty effect needs to be considered to strengthen memory and promote substantial changes (Reggev et al., 2018).

Given this, these initial results provoke essential questions that the stereotypes regarding smoking behaviors in the Chinese context may be affecting the design of anti-smoking campaigns, exacerbating disparities in public perceptions, leading in turn to inequalities in smoking prevalence or anti-smoking behaviors. For such reasons, it can be thus suggested that health practitioners need to think more about the diversity of both smokers and non-smokers, the differences in information and emotional needs between smokers and non-smokers, and the relative importance of gender roles in tobacco use in the traditional Chinese view. More importantly, the usual stereotype of smokers and selective attention have to be avoided, mainly providing a greater focus on females and non-smokers.

6.2.3. Differences in the total effect of anti-smoking information scanning on anti-smoking behaviors among population groups

In reviewing the literature, it was conclusively shown that inequalities in the exposure of health information ultimately impact an individual's decisions to engage in favorable health behaviors, thereby resulting in health disparities (Bigsby & Hovick, 2018; Viswanath et al., 2007). Although previous studies have noted the potential influence of social and individual determinants of health on public prevention behaviors, very little was found on how the total effect of anti-smoking information scanning via social media differed across population groups. Therefore, the multigroup analysis was employed in the second and third studies to assess whether the total effect of anti-smoking information scanning on social media users' anti-smoking behaviors was mediated by their social and individual determinants. The most unexpected finding to emerge from these studies is that the relationship between anti-smoking information scanning via social media and anti-smoking behaviors was not contingent on gender, age, monthly income, education, health literacy, and smoking characteristics of the participants. Notably, these results must be interpreted cautiously because the participants were divided into two subgroups in each division to facilitate the multigroup analysis. Besides, additional uncertainty arises from the measure of anti-smoking behaviors using self-reported actual behaviors rather than prolonged abstinence, such as 30-day or 6-month prevalence abstinence (Hughes et al., 2010; Luo et al., 2020).

In brief, while the aforementioned individual differences in scanning information acquisition regarding anti-smoking were empirically supported, the results obtained from multigroup analyses revealed that anti-smoking information scanning exerts equal influence on ultimate anti-smoking behaviors among different subgroups, especially among the disadvantaged group, such as the participants with lower income, education, and lower health literacy. Consequently, these analyses produced results in line with the findings of earlier studies, which revealed that the indirect effects of social and individual determinants through information scanning were smaller than their direct effects on health behaviors (Bigsby & Hovick, 2018). More importantly, despite there have varying conclusions about whether the effectiveness of anti-smoking messages differs by social and individual variables, what the current studies confirmed agreed with other research, which emphasized that social media-based health campaigns offered potential opportunities for improving general population health as well as decreasing health gap (Colston et al., 2021; Vereen et al., 2021).

There are several possible explanations for the same impact of anti-smoking information scanning on anti-smoking behaviors by social and individual determinants. Firstly, it may be explained by the fact that a wide variation of anti-smoking messages containing both informational and emotional support, not only expertise-based information but experience-based information, as well as containing multimedia content instead of text-only warnings, has been delivered through the universal channel in China. The content characteristics of anti-smoking messages mentioned above, which also were found in the first study of the current dissertation, have been recognized to be more effective among low-socioeconomic status groups, and these characteristics have been considered key elements to reducing disparities in smoking-related behaviors in prior studies (Bekalu et al., 2022; Colstion et al., 2021; Farrelly et al., 2012; van Meurs et al., 2022). Another possible explanation for this is that communication practitioners tend to convey simpler and more fragmented health content in ways that facilitates users' acceptance and attract more attention during their leisure time, not just for health information dissemination but for consumer engagement and marketing as well (Schreiner et al., 2021). Consequently, social media communicators have become aware of users' ability levels and personality traits, creating a more balanced health information environment for the entire population and disadvantaged groups (Niu et al., 2021).

It has been noted, furthermore, that there was a significant difference in the mean values of self-reported anti-smoking behaviors of the participants among a part of subgroups in the third study even though none of these differences in the total effect of anti-smoking information scanning were statistically significant, such as income group and health literacy group among non-smokers. As discussed above, these results may be due to communication disparities in exploring anti-smoking information on social media. However, another striking finding is that no significant differences in anti-smoking behaviors in age groups and health literacy groups among smokers in the third study were evident, even though communication disparities in anti-smoking information scanning were found across these groups. This inconsistency is in keeping with prior studies, whose contrasting conclusions about the relationship between communication disparities and health disparities, may be due to varying content types or differing study designs (Colston et al., 2021)

On the one hand, one of the issues that emerged from these findings is that such connections may exist between health communication inequities in access to online health information and disparities in anti-smoking behaviors, as elaborated in the structural influence model of communication (SIM) (Bekalu et al., 2022; Viswanath et al., 2007). Further research must incorporate additional measures to explore communication-related inequalities (such as health information seeking and health information discussing) rather than only assessing scanning information acquisition (Philbin et al., 2019). Moreover, additional studies need to be undertaken to validate the efficacy of the structural influence model of communication (SIM) by running moderated mediation process, specifically focusing on smoking-related behaviors in the Chinese context, which is an important issue for future research. On the other hand, all these findings and the discrepancies above may reflect the complexity of anti-smoking behaviors that an individual's decisions not only are oriented by the information environment but also are shaped by their living conditions and social surroundings. Also, these findings might help guide the creation of digital anti-smoking messages that, except for improvements in the accessibility of anti-smoking information, more effective content design strategies need to be adopted to create a favorable information environment as well as target intended groups who are less sensitive to anti-smoking messages (such as non-smokers) or who have been ignored for a variety of reasons (such as uses with lower socioeconomic status and female smokers).

6.3. Social media communication strategies for anti-smoking campaigns in China

In summary, all the findings obtained from the three central studies in the current dissertation can be summarized from the perspective of Lasswell's 5W model of communication (Lasswell, 1948) as follows:

1) Who (says) What (to) Whom (in) Which Channel:

The first study was designed to characterize the anti-smoking messages delivered through three popular social media platforms in China, including WeChat official accounts, Sina microblog platform, and TikTok, categorize more prominent themes and topics, as well as determining the differences in communicators, media types, and content types of anti-smoking messages among three channels.

Regarding communicators (Who says), the first study found that individual and governmental accounts posted more anti-smoking messages on the Sina microblog. In contrast, health and media accounts are posted more frequently through WeChat official accounts and TikTok.

Regarding the characteristics of anti-smoking posts on social media (says What), first of all, it can be categorized into six main themes and eight topics, including the hazards of smoking, tips tools and effective ways of smoking cessation, city news, and social activities, laws, and regulations regarding smoking control, benefits of smoking cessation, second-hand smoking, e-cigarette, and other relevant content. Notably, one of the most prominent findings is that the posts regarding the hazards of tobacco predominated on all three platforms. And the posts regarding tips, tools, and effective ways of smoking cessation are the second most prominent on WeChat, the posts regarding city news and social activities ranked second on the Sina microblog, and the posts concerning e-cigarettes were the second most prevalent on TikTok. Besides categorizing the themes and topics of anti-smoking messages, the first study set out with the aim of analyzing social support provisions (emotional support and informational support) and the basis of content (experience-based and expertise-based) as well. The important finding is that the anti-smoking posts containing informational support were more prevalent on WeChat official accounts and TikTok. In contrast, more emotional support was provided through the Sina microblog platform. In addition, more experience-based anti-smoking posts were delivered through the Sina microblog, but expertise-based anti-smoking posts were more prevalent on TikTok. And the anti-smoking posts based on experience and expertise were more prominent on WeChat official accounts. Additionally, another significant finding is that the anti-smoking posts containing multimedia were more frequent on WeChat than Sina microblog, and the pro-smoking posts were more common on the Sina microblog platform.

In general, the first study systematically analyzed what kind of anti-smoking information (says What) has been disseminated on TikTok, WeChat official accounts, and Sina microblog (in Which Channel) by which communicators (Who says) to clarify the information environment, which showed that more trustworthy and diverse anti-smoking information emerged. Indeed, it is difficult to explain the differences in the characteristics of anti-smoking pots among the three social media platforms. Still, it might be related to the different technical features of social media and users' motivations for using different platforms. In this regard, for instance, the Sina microblog is more visible and open that users tend to use it for achieving information gratifications, while WeChat is more relationship-focused that can fulfill users' affection gratifications (Gan, 2018; Jiang et al., 2021). And given the short video propagation mode, TikTok users were more likely to be motivated by fashion, entertainment, practical needs, and altruism (Xu, 2020). Hence, previous studies pointed out that self-presentation has been considered a key motivator behind Sina microblog use (Shu et al., 2017), providing some explanation as to why the proportion of pro-smoking messages, individual accounts, emotional support provisions, and experience-based messages was relatively higher on Sina microblog. In turn, there is no doubt that different social media platforms have different positioning, thereby creating different information environments and gathering different user groups that could partly explain these differences.

Regarding the characteristics of social media users (to Whom), the one-way ANOVA tests and Chi-square tests were conducted in the third study to analyze and compare the social media use (frequency of social media use, the choice of anti-smoking information sources, and the choice of social media platforms) of smokers and non-smokers, as well as their smoking characteristics (smoker types, the choice of tobacco products, TTF and CPD). Overall, these results demonstrated that male social media users, aged between 24 and 44, with higher educational attainment and higher monthly income, are more likely to be current smokers. Also, it has been found that the current male smokers over 32 and with higher monthly income are more likely to be everyday smokers and prefer regular cigarettes. And the male smokers and the smokers aged over 32 also reported smoking more cigarettes every day. Moreover, the current smokers who are female, aged between 18-31, or who reported lower monthly income are more likely to choose e-cigarettes. These results are consistent with the findings of other studies that focused on recent smoking intensity trends in China, such as Zhang et al. (2022) and Liu, S et al. (2020). Furthermore, in line with those of previous studies, these results confirmed that social media had become the major anti-smoking information source in China (Wang et al., 2021). In this respect, participants who reported higher monthly income and higher educational attainment tend to choose the Sina microblog. In comparison, lower-income individuals and smokers with lower educational levels prefer using WeChat official accounts. Meanwhile, non-smokers with lower education attainment or middle income are more likely to use TikTok. In addition, smokers who reported using e-cigarettes are more likely to use the Sina microblog, while smokers who prefer regular cigarettes tend to choose TikTok. In fact, the empirical findings above contribute in several ways to our better understanding of the priority of anti-smoking campaigns harnessing social media, providing a basis for designing more persuasive anti-smoking messages suited to different social media platforms.

2) With What effect:

The aforementioned analyses undertaken in the second and third studies based on the health belief model and the theory of planned model have identified how an individual was persuaded to perform anti-smoking behaviors through routine exposure to anti-smoking information on social media and how their awareness and perceptions were affected or guided. Annexes B combines the principal findings of these three studies, making a table.

6.3.1. Three focal points to guide social media communication strategies for anti-smoking

Based on the three studies in the present dissertation, these findings enhance our understanding of the anti-smoking information environment on TikTok, Sina microblog, and WeChat official accounts by using content analyses. Next, the current studies add to the growing body of research that demonstrates the differences in the characteristics of anti-smoking messages and users' profiles regarding social media use and smoking characteristics among three social media platforms. These findings might help us to determine the common features of the target audience of different social media platforms. Finally, these findings provide strong empirical confirmation about the impact of anti-smoking information scanning on social media users' anti-smoking behaviors by shaping their attitudes and perceptions. The results regarding the effectiveness evaluation and the differences in the proposed relationships should help us to determine which perceptions have to be promoted (also known as psychographics), which groups may be overlooked and what more efforts have to be made to ensure the effectiveness of anti-smoking information on social media (Schmid et al., 2008). More importantly, in accordance with the prior studies, these findings also have important implications for the necessity of anti-smoking message segmentation instead of universal strategies in the Chinese context, especially customizing and prioritizing relevant content (Bol et al., 2020; Parvanta et al., 2013; Stellefson et al., 2020). In line with these findings, three critical aspects have to be taken into account as follows (Jiang et al., 2021):

1) Anti-smoking messages characteristics:

Firstly, evaluating significant mediators between the anti-smoking information scanning via social media and anti-smoking behaviors has theoretical and practical implications for anti-smoking message design (Jiang & Beaudoin, 2016). Based on the second and the third studies, self-efficacy, behavioral attitudes, perceived barriers, and perceived severity have been key predictors of smokers' anti-smoking behaviors. In particular, self-efficacy is also a core motivator of non-smokers' anti-smoking behaviors. Therefore, anti-smoking messages delivered through three social media platforms have to be designed based on these findings. Following this line, the focal points of anti-smoking content refer to: a) convey more information regarding the seriousness of tobacco-related diseases, such as mortality rates; b) provide more practical information to help smokers overcome obstacles and negative emotions, including not only tips and effective ways of smoking cessation, but also how to cope with the social functions of smoking and c) create a favorable information environment and give more emotional support for enhancing smokers' and non-smokers' perceptions in their capability to perform anti-smoking behaviors. Notably, much of the literature has emphasized the positive and negative influence of fear appeals used in anti-smoking campaigns that can reinforce risk perceptions and persuade people to change their behaviors but may weaken confidence further (Manyiwa & Brennan, 2012; Nicolini & Cassia, 2021). Consequently, it is central to stress the negative health consequences of smoking by using feal appear without reducing individuals' self-efficacy.

Secondly, the present studies also have borne out the benefits of greater diversity, readability, quality, novelty, and originality of anti-smoking information that can reduce content homogeneity, ceiling effect, anti-smoking message fatigue, and even disparities in tobacco-related perceptions, thereby potentially changing the nonsignificant linkage and promoting desired health behaviors as well. These findings suggest that practitioners must be creative to make anti-smoking information more understandable, practical, and memorable by leveraging rich functionalities and the heterogenous nature of social media platforms, such as interactive engagement and multimedia tools.

2) Priority groups for anti-smoking campaigns on social media

As mentioned above, the nonsignificant association and significant differences in proposed relationships determined by the second and third studies can help us identify which groups have been generally neglected. For instance, despite a noticeable increase in the prevalence of tobacco use in younger generations and women, it is possible to assume that their needs are ignored due to the mean values of anti-smoking information scanning of these two groups being lower. Furthermore, the perceptions of female smokers regarding the seriousness of tobacco-related diseases were not affected by anti-smoking information scanning, while the female non-smokers' perceived susceptibility was significantly associated with anti-smoking information scanning because a majority of anti-smoking messages have been designed from a male perspective and female was presumed to be non-smokers in Chinese social context. Another often overlooked group is non-smokers, as our findings found that anti-smoking information doesn't exert influence on some subgroups of non-smokers, and the anti-smoking posts specifically focusing on second-hand smoking and how to remain a non-smoker are relatively less. Another concern is the effect of anti-smoking messages on addicted smokers. So, communicators need to pay more attention to changing their staunch views without resulting in defensive behaviors.

3) Culture appropriateness in anti-smoking campaigns

In designing anti-smoking messages, a vast amount of effort must be spent on understanding the cultural characteristics of smoking behaviors, tobacco education, and specific groups that can enhance the effectiveness of social media-based anti-smoking campaigns in China (Jiang & Beaudoin, 2016). Thus far, widely varying definitions of culture have emerged that tend to loosely reflect the values, beliefs, traditions, lifestyles, and norms of a given group (Hughes et al., 1993). In the literature, cultural beliefs and values have been widely recognized as central factors directly or indirectly influencing the adoption of health information and public health-related decisions, such as collectivism, familial roles, individualism, and communication patterns (Tan, & Cho, 2019).

Of importance, Kreuter et al. (2003) mentioned six culture appropriateness strategies in health communication, which can be summarized that health messages should be more accessible by using native language (linguistic strategies), more empirical by presenting the epidemiological data (evidential strategies), more attractive by considering the prior knowledge and experience of the population segments (constituent-involving strategies), more acculturated by focusing on internal content rather than exterior appearance (peripheral strategies) and by taking into account health issues from a sociocultural context (culture tailoring) (Tan, & Cho, 2019). To date, although the culture appropriateness strategies have become well-accepted, there is much less information about how these approaches have been applied to social media-based anti-smoking campaigns in China. There is abundant room for further investigations. In the present dissertation, except for determining which perceptions and attitudes can facilitate anti-smoking behaviors, we also provided some practical interpretations for why these mediators and pathways are statistically significant and non-significant. Consequently, the preceding interpretations lead to a primary thought of culture appropriateness strategies for anti-smoking campaigns in China.

Firstly, the first study's findings revealed that most anti-smoking messages disseminated on social media platforms were expertise-based content that cited the latest scientific data and was written in Chinese, coinciding with linguistic and evidential strategies. Secondly, multimedia health messages have been recognized as more effective in improving health outcomes and reducing health disparities. According to the first study, anti-smoking messages containing images and videos have been more frequently than text-only information on social media platforms. Peripheral strategies remind us that it is necessary to think critically about the increased usage of narrative entertainment and fragmented information for anti-smoking campaigns on social media. In other words, the balance between the enjoyment and rigorousness, the diversity and memorability, as well as the readability and depth of health information has been fluid and complex, rather than fixed and simple that health partitioners have to constantly pay attention to the variation on public opinions, health literacy, prior knowledge, and needs.

Thirdly, the presentation of anti-smoking messages should thoughtfully consider the special meanings, values, stereotypes, and even symbolism of smoking behaviors in Chinese society. Historically, tobacco has been considered a social currency because the gifting of expensive cigarettes can express respect, and some Chinese think it is rude to refuse an offered cigarette (Chu et al., 2011). In this regard, for instance, males have got more social benefits by providing or sharing cigarettes, that smoking symbolizes “a real man,” “a successful man,” and “a well-socialized man” in China. Meanwhile, in Chinese tradition, female smokers have been regarded as rude. The traditional thoughts hold that married women should take more responsibility for childcare than married men so that they shouldn’t and won’t smoke (Zhang et al., 2022). These stereotypes and traditional beliefs provide some explanation as to why a female might be assumed to be a passive smoker so that female smokers’ perceived severity was not affected by anti-smoking information scanning in the third study. Still, female non-smokers’ perceived susceptibility was promoted. In line with culture tailoring strategies, considering gender distinction and traditional beliefs is imperative that it requires painstaking attention to respect the female perspective of tobacco use and offer customized anti-smoking messages to match the profile of female smokers. Besides considering smoking imagery in Chinese society, the possible rise of individualism in contemporary China has to be taken into account because self-efficacy has been found to be a more important predictor among all subgroups of smokers and non-smokers rather than subjective norms. Within a rapidly changing society context, cultural orientation sheds light on the choice of self-or other-directed anti-smoking messages and individualistic or collectivist fear appeal (Lee & Park, 2012; Li, 2017).

6.3.2. Targeting communication strategies to a specific social media platform

After clarifying the general guidance for developing social media communication strategies for anti-smoking campaigns in China, the final section draws together these various findings to put forth more specific strategies targeting three social media platforms., including WeChat official accounts, Sina microblog, and TikTok.

1) WeChat official accounts

Based on our findings, the primary target audience of anti-smoking campaigns harnessing WeChat official accounts refers to the participants with lower educational attainment or monthly income, the non-smokers, and the smokers who are more likely to use regular cigarettes. To some extent, WeChat official accounts can be regarded as the main battlefield for delivering anti-smoking campaigns for Chinese non-smokers and disadvantaged groups and reducing smoking initiation.

According to the results that non-smokers reported relying more on traditional media to obtain anti-smoking information, and the anti-smoking posts about the hazards of smoking and effective ways of smoking cessation predominated on the WeChat platform rather than information specifically focusing on non-smokers, more attractive anti-smoking messages matching the informational and emotional needs of non-smokers have to be delivered in the future. For example, it has to concentrate on promoting male non-smokers' perceived susceptibility by disseminating more anti-smoking information regarding the negative consequences of secondhand smoke via WeChat official accounts. The other focal point emphasizes how to stay smoke-free and protect themselves. Additionally, as the anti-smoking posts containing informational support and expertise-based information have been more prevalent on WeChat, it is necessary to use a more emotional tone and storytelling to enhance the self-efficacy of non-smokers, which has been determined as the only significant mediator between the anti-smoking information scanning and non-smokers' anti-smoking behaviors.

Targeting the smokers with lower educational levels and monthly income, anti-smoking messages delivered through the WeChat official accounts have to be more understandable and memorable, continuing to using multimedia tools and propagating the hazards of tobacco use and effective ways of smoking cessation, such as the seriousness and the incidence of tobacco-related diseases, because the mean values of perceived susceptibility and perceived severity of smokers with lower monthly income have found to be significantly lower whereas their perceived barriers were higher.

2) Sina microblog platform

Compared to WeChat official accounts, smokers, especially those with higher monthly income and educational attainment and who prefer e-cigarettes, reported using the Sina microblog platform more frequently to obtain anti-smoking information. Meanwhile, the pro-smoking messages have been more prevalent on the Sina microblog. Hence, in a way, Sina microblog platforms have to be considered the critical battleground in combating pro-smoking messages and providing more informational support and expertise-based information by showing more epidemiological data for the current smokers.

Regarding the main themes of anti-smoking posts on the Sina microblog, except the existing content about the hazards of smoking, city news, and social activities, more posts relevant to the practical ways of smoking cessation and e-cigarettes have to be delivered. As smokers with higher socioeconomic positions also reported higher health perceptions and health literacy, health practitioners need to pay more attention to the ceiling effect and anti-smoking messages fatigue, as mentioned above. More importantly, another challenge is how to stimulate addicted smokers effectively. In this regard, message novelty and more usage of multimedia tools need to be considered. Additionally, health and media accounts must be much more involved in tobacco education, harnessing the Sina microblog platform. Notably, our findings point out that the engagement level of anti-smoking messages on the Sina microblog platform is the lowest among the three channels. Hence, health practitioners have to effectively use the hashtag, deliver updated content and, more importantly, cooperate with key opinion leaders on the Sina microblog platform to facilitate greater anti-smoking information diffusion and maximize engagement, thereby ensuring a broader audience is being reached, especially younger generations.

3) TikTok

With the noticeable number of TikTok users in China, especially among the younger generations, and the relatively higher proportion of TikTok usage among the participants in the current dissertation, we can infer that TikTok will act as a central communication tool for tobacco use prevention and control soon. According to our findings, the primary target audience of anti-smoking campaigns harnessing TikTok refers to the smokers who reported using regular cigarettes more frequently and a part of non-smokers who reported having a middle monthly income. From this perspective, more short videos focusing on everyday cigarette use must be generated rather than e-cigarettes.

Based on the results derived from the content analyses, it noted mentioning that one of the advantages of anti-smoking posts on TikTok is that the content based on both personal experience and expertise has been more prevalent compared to the other two platforms. And the descriptive analysis also revealed that the users' engagement level with anti-smoking information on TikTok is the highest due to its interactive features and short video propagation mode. Hence, official accounts, especially governmental accounts, must leverage the obvious advantages of TikTok for anti-smoking propaganda.

CHAPTER 7

Conclusion

7.1. Summary and implications

7.1.1. What is already known?

Globally, tobacco use has become one of the greatest risk factors for preventable mortality and various chronic diseases. Especially in China, the tobacco epidemic remains a major public health concern and the leading cause of substantial death. Although the smoking prevalence worldwide has declined over the past half-century due to the considerable efforts made by public health agencies of many countries, there is an urgent need to set up anti-tobacco media campaigns within the recent trends in tobacco addiction among adults and e-cigarette use among younger generations. It noted that the primary purposes of an anti-smoking campaign include not only promoting quitting attempts but also reducing tobacco use initiation and encouraging everyone to persuade smokers to stop smoking.

In recent years, despite literature offering contradictory findings about the association between social media use and health behaviors due to a more complex information environment caused by online misinformation or information overload, results from numerous studies still provided empirical evidence that health campaigns harnessing social media platforms have effectively contributed to better health outcomes among the general populations. In previous studies focusing on the effectiveness of tobacco education, it has been conclusively shown that users' knowledge level, awareness, and risk perceptions of tobacco use can be promoted by a wide range of anti-smoking information disseminated on social media. Based on the conclusions from the prior studies, social media platforms can gather diverse anti-smoking messages and trusted information sources, amplify the diffusion of knowledge, create interactive space, and provide both emotional and informational support for smokers, thereby promoting public engagement in anti-smoking behaviors.

Consequently, the research to date has been concerned with the relationship between users' communication behaviors on social media and their actual health behaviors in real life because behavioral changes have been regarded as the essential criteria in the effectiveness evaluation of a health campaign. For exploring the underlying behavioral mechanism, the health belief model (HBM) and the theory of planned behavior model (TPB) have been proposed and widely evaluated, including valuable mediators reflecting an individual's perceptions and attitudes from different angles. Communication behaviors on social media platforms can be divided into one-way and two-way information usage patterns. One-way information usage patterns refer to information scanning and information seeking, and two-way information usage pattern refers to interactive activities, such as comment and discussion. Information scanning, which is different from intentionally information seeking, is defined as incidental and passive information acquisition that is far common during the routine use of social media, exerting significant influence on health decision-making. However, what is not yet clear is how information scanning behaviors via social media affect health behaviors.

Indeed, a search of the literature also revealed that social and individual determinants affect social media usage (e.g., digital divide and usage divide), communication behaviors (e.g., information acquisition and engagement behaviors), and health outcomes as well (e.g., perceptions and behaviors). Hence, in this regard, prior studies have proposed the structural influence model of communication (SIM) with the aim of better understanding the mediation effect of social determinants on the relationship between communication behaviors and health behaviors, targeting disadvantaged groups and reducing health disparities.

Considering all this evidence, these studies highlight the beneficial effect of anti-smoking campaigns harnessing social media, provide reasonably consistent evidence of an association between anti-smoking information acquisition and anti-smoking behaviors, and indicate that an individual’s perceptions and attitudes often serve as significant predictors of desirable behaviors. In addition, the literature reviewed here suggests a more comprehensive thought of the roles of social and individual determinants.

7.1.2. What does this dissertation add?

Overall, the present dissertation includes three central studies: 1) Content analysis of anti-smoking posts on social media in China; 2) The impact of anti-smoking information scanning on anti-smoking behaviors of social media users in China: based on the TPB model and 3) Passive anti-smoking information acquisition via social media and anti-smoking behaviors in China: based on HBM and SIM model.

First of all, this dissertation seeks to clarify the anti-smoking information environment of social media in China by systematically investigating the characteristics of anti-smoking posts disseminated through WeChat official accounts, TikTok, and Sina microblog. After ascertaining the content type, communicators, media type, and central themes of anti-smoking posts in the first study, the second and the third studies were set out to remedy the central questions in this dissertation about how anti-smoking information scanning behaviors via social media affect users’ actual anti-smoking behaviors by evaluating the health belief model and the theory of planned behavior model, respectively. In these two studies, some comparison analyses were conducted to determine the differences in pathways connecting anti-smoking information scanning and anti-smoking behaviors in various population subgroups, such as younger versus elder, smokers versus non-smokers, and females versus males. Also, the third study was designed to measure whether social and individual determinants have an influence on anti-smoking information scanning and also explore in detail the characteristics of Chinses social media users in terms of smoking behaviors.

Characterization of anti-smoking posts is vital for our increased understanding of what types of content have been generated, delivered, and provided through popular social media platforms in China. It can also explain both significant and non-significant linkages in the proposed frameworks. According to the first study, the results revealed that the anti-smoking posts disseminated on three social media platforms have similarities and differences. In this vein, the posts regarding the hazards of tobacco use have predominated on all three platforms. Media and health accounts delivered more anti-smoking information, and informational support provisions were more frequent via WeChat official accounts and TikTok. Besides, the majority of anti-smoking posts were attached with multimedia. Regarding the differences, our findings indicated that pro-smoking information, emotional support provisions, and experience-based content were more common, and the individual and governmental accounts make the greater voice on the Sina microblog than on the other two platforms.

Returning to the central questions posed at the beginning of the present dissertation, it is now possible to state that anti-smoking information scanning via social media platforms exerts a positive influence on the ultimate anti-smoking behaviors of social media users by shaping an individual's health perceptions and attitudes. By evaluating the health belief model and the theory of planned behavior model in the Chinese context, these findings strengthen the idea that both smokers and non-smokers have greater perceptions due to broader anti-smoking information dissemination across a wide variety of social media platforms, thereby promoting better behavioral performance. In other words, both studies have examined the direct impact of anti-smoking information scanning that the various readable and attractive anti-smoking information make users understand, memorize and absorb more easily. In this aspect, one of the more interesting findings to emerge from these two studies is that based on the health belief model and the theory of planned behavior model, seven constructs regarding the smokers' perceptions and attitudes are significantly affected by anti-smoking information scanning via social media. Still, among non-smokers, their perceived susceptibility was not influenced by the unintentional acquisition of anti-smoking information. Next, the findings about whether these perceptions and attitudes converted into actual anti-smoking behaviors varied between smokers and non-smokers. In this respect, perceived barriers, perceived severity, self-efficacy, and behavioral attitudes emerged as imperative preconditions of smokers' anti-smoking behaviors. In contrast, self-efficacy was the only significant mediator between the non-smokers' anti-smoking information scanning and anti-smoking behaviors.

Then, these studies also examined the differences in the mean values of anti-smoking information scanning and the path coefficients of proposed relationships by conducting multiple regression and multigroup analysis. Multiple regression analysis revealed that social and individual determinants are associated with anti-smoking information scanning behaviors of smokers and non-smokers, including monthly income, health literacy, self-reported health status, and age. Notably, the communication disparities in the exposure of anti-smoking information were not caused by the differences between those who have access to digital media and those who don't have, or the social media use intensity. An implication of the small effect size (R^2) is the possibility that users' lifestyles, social surroundings, personal experience, prior knowledge, filter bubble hypothesis, and even self-recall bias may have influenced their passive anti-smoking information acquisition.

Regarding the observed differences in the impact of anti-smoking information scanning on an individual's perceptions and its total effect on anti-smoking behaviors by the population subgroups, the findings provide important insights into the role of social media platforms in reducing disparities in tobacco-related perceptions by disseminating understandable and more uncomplicated anti-smoking messages to a broader audience because most of the differences in the proposed relationships were not observed. However, one of the more significant findings to emerge from these studies is that the impact of anti-smoking information scanning on perceived severity, perceived susceptibility, and perceived barriers varied between females and males. Therefore, these differences that we have identified assist in our understanding of the importance of giving full consideration to gender distinction and stereotypes regarding tobacco-related behaviors in the Chinese social context. In addition, these analyses also found non-significant relationships between anti-smoking information scanning with the health cognitions of addicted smokers and a part of non-smokers. These findings may capture different perceptions and attitudes of the population subgroups so that health practitioners can design digital anti-smoking messages more suited to population segments.

Regarding the differences in the total effect of anti-smoking information scanning, these results agree with the findings of other studies indicating that its total effect didn't vary among the population subgroups, which showed that the richness and diversity of anti-smoking messages delivering through social media could contribute to reducing health disparities as well as promoting general health outcomes. Although this study focuses on the effectiveness evaluation of anti-smoking information scanning via social media, the findings may have a bearing on the relationship between communication disparities and health disparities in tobacco education. The results broadly support the earlier observations, which revealed that social determinants could shape access to health information. However, the findings about whether communication disparities lead to health disparities are contradictory. These discrepancies suggest that further research is required to ascertain the origins of health disparities in anti-smoking behaviors.

Developing health communication strategies should be theory-based to apply these findings to deliver more persuasive anti-smoking messages on social media targeting (group-based) or tailoring (individual-based) to significant predictors and pathways derived from the proposed hypotheses. In other words, by evaluating the direct and indirect effect of anti-smoking information scanning among both smokers and non-smokers based on the health belief model and the theory of planned model, as well as conducting an in-depth analysis of differences in path coefficients, anti-smoking information scanning, social media use, and smoking characteristics of the participants, more detailed audience segmentation strategies can be developed that the social media users have been divided into more homogenous subgroups by determining not only their perceptions and psychological characteristics, but also their demographic and other relevant characteristics. On the one hand, as the content characteristics, such as social support, media types, topics, and communicators, have an impact on public engagement online and offline, these findings suggest that health practitioners have to deliver more persuasive anti-smoking information which could contribute to general changes in terms of risk perceptions, perceived barriers, and self-efficacy, as well as considering about the novelty effect, originality, fear appeals, creativity, quality of anti-smoking posts. On the other hand, health practitioners must emphasize the complexity of female smokers, younger generations, non-smokers, and addicted smokers on this basis, as well as consider gender distinction, stereotypes, cultural characteristics, and the ceiling effect.

7.1.3. What are the contributions and implications for research and practice?

From a theoretical perspective, firstly, this dissertation has been one of the first attempts to thoroughly analyze what anti-smoking information has been disseminated on three popular social media platforms in China by using quantitative approaches. On the one hand, we recruited anti-smoking posts not only from the Sina microblog but also from WeChat official accounts and TikTok to date, and there have been few empirical investigations into anti-smoking information propagation on these two platforms. On the other hand, the analyses undertaken here explored different characteristics of anti-smoking posts that focused on its communicator, social support provisions, the basis of content, topics, and media type, thereby expanding our understanding of what types of anti-smoking information can be acquired by social media users as well as providing a basis for the following work to identify its potential impact.

Second, communication and health behavior associations have been examined in two ways: the health belief model and the theory of planned behavior model, which can help us to improve the predictions of the effectiveness of information scanning behaviors. Indeed, our dissertation provides empirical evidence for the direct and indirect impact of unintentional information acquisition instead of information seeking or discussing, filling the literature gap. And the application of these two models assists in a more profound understanding of the significant mediators between anti-smoking information scanning and anti-smoking behaviors. More importantly, one of the strengths of this dissertation is that it represents a comprehensive examination of the whole group of social media users, considering several social and individual determinants. In this regard, although extensive research has been carried out on the mediation effect of sociodemographic variables on the proposed relationships, most of these studies have been restricted to a limited comparison of smokers and non-smokers. What is not yet clear is the smoking characteristics of Chinese social media users. Therefore, the dissertation presented here makes a significant contribution to research by grouping social media users into more homogenous segments and examining differences in pathways because the effectiveness evaluation of anti-smoking information scanning might be incomplete and unclear without considering the characteristics of social media users.

Third, to the best of our knowledge, this is the first study to combine the structure influence model of communication (SIM) with the health belief model to investigate the association between communication behaviors and anti-smoking behaviors, as well as explore the roles of social and individual determinants. As mentioned above, the present dissertation provides partial support for the SIM framework within the Chinese context that confirms prior findings concerning the association between communication behaviors and health behaviors and demonstrates the communication disparities caused by social and individual variables. Consequently, further work needs to be done to establish whether communication disparities contribute to health disparities in anti-smoking behaviors by measuring conditional indirect effects based on the findings and implications derived from the present dissertation.

From a practice point of view, these findings are relevant to communication researchers and public health practitioners. Of those that do, these findings show a clear-cut positive effect of anti-smoking information on anti-smoking behaviors of smokers and non-smokers and highlight the potential usefulness of social media in promoting tobacco control and reducing health disparities. There is, therefore, a definite need for taking advantage of social media platforms to create a favorable information environment and deliver more persuasive anti-smoking messages to a broader audience. In particular, the noteworthy findings related to the significant mediators between anti-smoking information scanning and anti-smoking behaviors can help us determine which kind of content should be delivered more frequently. Additionally, these particular research findings also point to the need for anti-smoking message segmentation that the practitioners have to develop targeted anti-smoking information aimed at different social media platforms and various subgroups. As a series of comparison analyses revealed which population segments should receive priority attention, continued efforts are needed to make anti-smoking information more accessible to neglected groups, such as female smokers and non-smokers. In developing communication strategies for anti-smoking campaigns harnessing social media, more outstanding efforts are needed to ensure that gender distinction and sociocultural context are considered.

7.2. Limitations and future needs

Several limitations to this dissertation need to be acknowledged. First, although the sample size is relatively large, it was impossible to assess the differences in pathways between higher and lower education levels due to the lack of enough participants with high school graduates or below. Similarly, it is unfortunate that the study did not include social media users aged over 63 years or differentiate between the participants living in rural areas and those living in urban areas. Further studies are required to investigate based on a nationally representative sample. Second, the other source of weakness in these studies was that we used a single item to measure the perceived benefits, perceived severity, and subjective norms. Also, the responses relating to anti-smoking information scanning and anti-smoking behaviors were subjective and were, therefore, susceptibility to recall bias. Third, for ensuring similar sample sizes in the Chi-square tests and conducting multigroup analyses, sometimes there are only two subgroups in each division. These findings must be interpreted with caution. Even though this dissertation has successfully demonstrated the positive effect of anti-smoking information scanning via social media on anti-smoking behaviors, it has thrown up many questions in need of further investigation. First, further research could assess the long-term effects of anti-smoking information scanning by following up on prolonged abstinence rather than measuring self-reported actual anti-smoking behaviors. Second, more studies should attempt to address the questions raised by this dissertation, such as evaluating whether communication disparities lead to health disparities based on the structural influence model of communication, seeking to minimize bias by self-reported data, and investigating what kind of content characteristics of anti-smoking information exerts greater influence on public health outcomes. Third, another possible area of future research would be to investigate how anti-smoking information's impact varied among social media platforms. Finally, a greater focus on the combined effect of information seeking and scanning could produce interesting findings. In conclusion, it is hoped that this dissertation can advance our knowledge of social media use in tobacco education within the context of Chinese society.

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Annexes A

iscte INSTITUTO UNIVERSITÁRIO DE LISBOA

COMISSÃO DE ÉTICA

PARECER [Final] 95/2021

Projeto "The impact of anti-smoking information scanning via social media on smoking cessation behaviors in China"

O projeto *"The impact of anti-smoking information scanning via social media on smoking cessation behaviors in China"*, submetido pelo investigador Cheng Cheng, coordenado pela Prof. Rita Espanha, foi apreciado pela Comissão de Ética (CE) na reunião de 8 de julho de 2021.

A apreciação do projeto suscitou, porém, algumas reservas plasmadas no Parecer [Intercalar] 95/2021, em relação às quais os investigadores vêm agora prestar esclarecimentos adicionais, que a Comissão de Ética entende satisfazerem os requisitos éticos exigíveis, não obstante algumas recomendações:

1) Não obstante as explicações providenciadas pelos investigadores, os termos e avisos de privacidade fornecidos, relativos ao software para a recolha de dados, estão redigidos em mandarim, pelo que a CE desconhece o seu conteúdo. Acresce que embora os investigadores garantam que o software garante a recolha de dados de forma anónima (falamos do software propriamente dito, e não se as questões no questionário recolhem ou não dados pessoais), a CE desconhece possíveis limitações ao anonimato/confidencialidade no quadro jurídico do país onde os dados vão ser recolhidos. Cabe, pois, aos investigadores assegurar a mitigação de eventuais riscos, caso eles existam.
2) Os documentos fornecidos em inglês têm diversos problemas de redação/linguagem, que se impunham ser corrigidos. Contudo, uma vez que os documentos finais serão redigidos em mandarim, a CE assume que os investigadores assegurarão a boa tradução e redação dos textos.
3) A CE sugere a remoção da seguinte frase do debriefing, "*If there have symptoms of anxiety or depression caused by tobacco use, you should be in a timely manner to a regular hospital*", uma vez que se afigura poder vir a ser mal entendida e, porventura, induzir ansiedade nos participantes.

Em suma, assegurados que se encontram a natureza voluntária da participação, e tendo os investigadores assegurado que se encontram garantidos o anonimato e a confidencialidade dos dados coligidos, entende a Comissão de Ética emitir parecer final favorável à realização da investigação, sem prejuízo das recomendações e observações referidas.

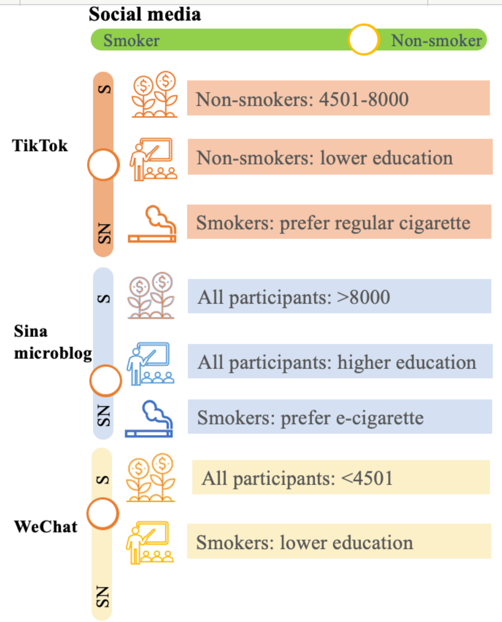
Relator: Nuno David (com Cecília Aguiar)

Lisboa, 18 de Julho de 2021

O Presidente da Comissão, *Professor Doutor Sven Waldzus*

O Relator, *Professor Doutor Nuno David*

Annexes B

			Social media			Traditional media
			TikTok	Sina microblog	WeChat official accounts	
Disseminated anti-smoking messages	Topic	1º	The hazards of smoking			
		2º	E-cigarette	City news and social activities	Tips, tools and effective ways	
	Communicator	1º	Media	Individual	Health	
		2º	Health	Governmental	Media	
	Basis of content	1º	More expertise+experience-based	More experience-based	More expertise-based	
	Social support	1º	More informational support	More emotional support	More informational support	
	Media type	1º	100% short videos	Less multimedia	More multimedia	
Target audience	Social media users					
			Smokers		Non-smokers	
Perceptions&attitudes	IN		↓		↑	
	PBE		—		—	
	PBA		↑		↓	
	PSE		↑		↓	
	PSU		↑		↓	
	SE		↑		↓	

		Social media	Traditional media
	B	⬆️	⬇️
Effective mediators	**SN**	❌	❌
	BA	✅	❌
	SE	✅	✅
	PBE	❌	❌
	PBA	✅	❌
	PSE	✅	❌
	PSU	❌	❌