Let's get intimate: social media practices of age-diverse audiences and their preferences related to micro-influencer health and wellbeing message strategies

Victoria Taddeo

Bachelor of Business (Marketing)

Diploma in Languages

Thesis Submitted for the Degree of Masters by Research

June 2023

Supervision Team:

Dr Ryan Tang, Professor Allan O'Connor, Associate Professor Lisa Schuster

UniSA Business

University of South Australia

Table of Contents

Acknowledgements ..... ***vii***

List of Figures ..... ***ix***

List of Tables ..... ***x***

Abbreviations ..... ***xii***

Abstract ..... ***xiii***

Declaration ..... ***xv***

Chapter One: Introduction and Thesis Overview ***1***

1.1. Research Context **1**

1.2. Research Aim and Questions **5**

1.3. Methodology **6**

1.4. Key Findings **7**

1.5. Thesis Structure **8**

Chapter Two: Literature Review ***9***

2.1. The Rise of Social Media for Marketing **9**

2.1.1. Defining Social Media 9

2.1.2. Social Media as an Avenue for Marketing 10

2.1.3. Social Media Marketing for Health and Wellbeing Messages 12

2.2. Influencer Marketing, Digital Influencers, and Micro-influencers **14**

2.2.1. Influencer Marketing and Digital Influencers 14

2.2.2. Micro-influencers as a Marketing Strategy 18

2.3. Social Media Users **19**

2.3.1. Social Media User Demographics and Practices of Age-diverse Audiences 19

2.4. Theoretical Underpinnings: Media Richness Theory **22**

2.5. Social Media Message Strategies 25

2.5.1. Social Media Platforms 25

2.5.2. Social Media Message Formats 27

2.5.3. Social Media Message Types 29

2.6. Social Media Message Strategy Preferences of Social Media Users 33

2.6.1. Preferences of Social Media Platform 33

2.6.2. Preferences of Social Media Message Format 36

2.6.3. Preferences of Social Media Message Type 37

2.7. Chapter Summary 41

Chapter Three: Methodology 43

3.1. Research Design 43

3.2. Method: Cross-sectional Online Survey Incorporating Discrete Choice Experiment 45

3.2.1. Stated Preference Approach and Discrete Choice Experiment 45

3.2.2. Discrete Choice Experiments and Random Utility Theory 48

3.2.3. Discrete Choice Experiment Steps 49

3.3. Online Cross-sectional Survey Design 56

3.3.1. Online Survey Testing and Piloting 59

3.4. Sampling and Participant Recruitment 60

3.4.1. Sampling 60

3.4.2. Participant Recruitment Strategies 61

3.5. Ethical Considerations 62

3.5.1. Ethics Approval 62

3.5.2. Participant Consent 63

3.6. Sample Survey Screening and Sample Demographics 63

3.6.1. Sample Screening 63

3.6.2. Sample 64

3.7. Data Analysis 68

3.7.1. Data Cleaning and Preparation 68

3.7.2. Data Analysis Techniques 69

3.8. Chapter Summary 73

Chapter Four: Empirical Results 74

4.1. Sample by Age Categories and Social Media Practices 76

4.1.1. Number of Social Media Accounts with Different Social Media Platforms 76

4.1.2. Active Social Media User 79

4.1.3. Most Utilised Social Media Platforms 80

4.1.4. Technological Devices Used for Social Media 83

4.1.5. Time Most Active on Social Media 86

4.1.6. Frequency of Social Media Use 89

4.1.7. Social Media Activities 91

4.2. Followers of Micro-influencers by Social Media User Practices 93

4.2.1. Followers of Micro-influencers 94

4.2.2. Non-followers of Micro-influencers 95

4.2.3. Reasons for Following Micro-influencers 96

4.2.4. Social Media Platforms Used to Follow Micro-influencers 97

4.3. Followers of Micro-influencers by Social Media Message Strategy Preferences 100

4.3.1. Followers of Micro-influencers by Social Media Platform Preferences 100

4.3.2. Followers of Micro-influencers by Social Media Message Format Preferences 103

4.3.3. Followers of Micro-influencers by Social Media Message Type Preferences 106

4.3.4. Followers of Micro-influencers by Impact of Varying Topics on Message Strategy Preferences 108

4.4. Discrete Choice Experiment 110

4.4.1. Analysis of Discrete Choice Experiment Data 110

4.4.2. Discrete Choice Experiment Results 111

Chapter Five: Discussion and Conclusion 119

5.1. Social Media Practices of Age-Diverse Audiences (RQ1) 120

5.1.1. RQ1 Summary of Key Findings 121

5.1.2. Number of Social Media Accounts 122

5.1.3. Active Social Media Use 123

5.1.4. Social Media Platforms Most Active 124

5.1.5. Device Used to Access Social Media 125

5.1.6. Time of Day Most Active on Social Media 125

5.1.7. Frequency of Social Media Use 126

5.1.8. Social Media Activities 127

5.1.9. Followers and Non-followers of Micro-influencers 128

5.1.10. Motives for Following Micro-influencers 129

5.1.11. Social Media Platforms Used to Follow Micro-influencers 129

5.2. Social Media Message Strategy Preferences of Age-diverse Audience (RQ2) 130

5.2.1. RQ2 Summary of Key Findings 131

5.2.2. Social Media Platform Preferences of an Age-diverse Audience (RQ2a) 131

5.2.3. Social Media Message Format Preferences of an Age-diverse Audience (RQ2b) 133

5.2.4. Social Media Message Type Preferences of an Age-diverse Audience (RQ2c) 134

5.3. Social Media Message Strategy Preferences by Age Categories and Social Media Platforms (RQ3) 136

5.3.1. RQ3 Summary of Key Findings 136

5.3.2. Message Strategy Preferences by Age Categories 136

5.3.3. Message Strategy Preferences by Social Media Platform Preference 139

5.4. Theoretical Contributions 140

5.5. Industry and Social Implications 144

5.6. Strengths and Limitations of the Study 151

5.7. Directions for Future Research 153

5.8. Conclusion 154

References 156

Appendices 171

Appendix A: University of South Australia Ethics Approval 171

Appendix B: Online Survey and Information Sheet 172

Appendix C: Discrete Choice Experiment Presentation in Survey 194

Appendix D: Recruitment Material 200

Appendix E: SAS Output 203

Acknowledgements

To my supervisors, Ryan, Allan, and Lisa. I would like to extend my deepest and upmost gratitude to each of you for your support throughout my Masters. To Ryan, thank you for the time and support you have given me throughout this journey which has been instrumental in helping me to complete this thesis. To Allan, for whom I would not be here without. Thank you for your leap of faith in taking me on and for all the opportunities you have given me over the last three years. To Lisa, thank you for your encouraging words, advice, and feedback which helped strengthen my thesis. Your valuable insights were always very much appreciated.

Thank you also to Marianna who supported me in the initial stages of my research development. A big thank you to Cathie and everyone in the UniSA Business HDR support team for your amazing support throughout the process. Thank you to my peers and wonderful officemates, Ruth and Kathie for the encouraging and supportive chats.

Thank you also to my industry supervisor Ivan for the opportunities you have given me and for always making the time to meet up for a chat about my thesis and about life generally.

To my family. Mum, where to even begin, I'm not sure I would have made it to this point if not for you. Your support in all its many and endless forms is something I cannot thank you enough for. I am so grateful to you and Dad for always supporting me and giving me the best upbringing that allowed me to have the opportunities I have been lucky enough to experience.

To Jessica, Elizabeth, and Stav, thank you for always listening to me vent and keeping me company, even into the late nights, when I was working. Thank you for always keeping it real with me but saying the right things to keep me calm.

To Nonna and Nonno, thank you for your endless words of encouragement and unwavering faith in me, your fierce words of 'you can do it' whenever I was having a down moment kept me going.

To Javier, thank you for always listening to me to go on and on, for always being by my side, motivating me, and giving me the push to keep going, especially at the end. Thank you for being a calming voice of reason during the hard moments.

To my best friends, Ellie, Hitha, Joanne, and Tash, thank you for listening to me ramble on about my thesis and for taking my mind off the stresses each week. Thank you for sticking by me for not only the past 2 years, but for the past 20 years, I don't know where I would be without your friendship and support.

Importantly, thank you to the participants who took part in my study, your time was very much appreciated. I also wish to acknowledge the support of an Australian Government Research Training Program Scholarship.

List of Figures

Figure 1: Conceptual model: audience age and social media platform (using social media platform preference) moderates audiences' message strategy preferences 42

Figure 2: Stated preference methods (Merino-Castello, 2003)..... 47

Figure 3: Steps and phases in a discrete choice experiment (adapted from Turner & Coote, 2017)..... 50

Figure 4: SAS output 54

Figure 5: Presentation of a discrete choice experiment choice set in Qualtrics survey 59

Figure 6: Age (years) by total sample 65

Figure 7: Example of dummy coding and preparation of data for discrete choice analysis ... 72

List of Tables

Table 1: Categories of message type 33

Table 2: Literature review 38

Table 3: Attributes and levels for discrete choice experiment 52

Table 4: Discrete choice experiment choice sets 55

Table 5: Age categories by generation 61

Table 6: Summary of total sample demographics 64

Table 7: Cross-tabulation of age categories and gender 66

Table 8: Summary of discrete choice participants' demographics 67

Table 9: Interpretations for Cramer's V (Cohen, 1988) 76

Table 10: Chi-square results of age categories and number of social media accounts held by a participant 78

Table 11: Chi-square results of age categories and active users 80

Table 12: Frequencies: social media platforms participants are most active on 81

Table 13: Cross-tabulation of age categories and most utilised social media platforms 82

Table 14: Chi-square results of age categories and top three most utilised social media platforms 83

Table 15: Cross-tabulation of age categories and devices used to access social media 85

Table 16: Chi-square results of age categories and devices used to access social media 85

Table 17: Cross-tabulation of age categories and time most active on social media 87

Table 18: Chi-square results of age categories and time most active on social media 88

Table 19: Chi-square results of age categories and frequency of social media access 90

Table 20: Cross-tabulation of age categories and social media activities 92

Table 21: Chi-square results of followers of micro-influencers by age categories 95

Table 22: Chi-square results of likely to follow micro-influencer in the future and age categories 96

Table 23: Cross-tabulation of age categories by reasons for following micro-influencers..... 97

Table 24: Cross-tabulation of age categories by social media platforms used to follow micro-influencers 99

Table 25: Chi-square results of age categories by follow micro-influencer on more than one social media platform 100

Table 26: Frequencies of preferred social media platform 101

Table 27: Cross-tabulation of age categories by preferred social media platform 102

Table 28: Chi-square results of age categories by preferred social media platform 103

Table 29: Chi-square results of age categories by preferred social media message format 104

Table 30: Chi-square results of age categories by preferred social media message format when thinking of social media platform preference 105

Table 31: Chi-square results of age categories and preferred social media message type.. 106

Table 32: Chi-square results of age categories by preferred social media message type when thinking of social media platform preference 108

Table 33: Chi-square results of age categories by preferred message strategy (MS) differ depending on message topic 109

Table 34: Model 1 – Attributes only 111

Table 35: Model 2 – interaction effects: message formats and message types x age category 113

Table 36: Model 3 – interaction effects: message formats and message types x social media platforms (by platform preferences) 116

Table 37: Findings and Implications 147

Abbreviations

Coef. – Coefficient

M – Mean

Mdn – Median

SD – Standard Deviation

SE – Standard Error

Abstract

Over the past two decades, widespread technological advances and an increased uptake of technology has led to a growing number of age-diverse online users, especially older age groups. Developments and an expanded digital infrastructure has also led to considerable growth in digital marketing practices. This includes online influencer marketing, whereby digital influencers are increasingly leveraged to engage, educate, promote or raise awareness about a range of topics, such as health and wellbeing, on social media platforms. In response to an ageing population, governments have identified digital inclusion and healthy ageing as key policy priorities (Office for Ageing Well, 2019). With age demographics increasing online, and with the growing appeal of micro-influencers – digital influencers who have a relatively small number of followers and can intimately connect with audiences – there is an imperative to leverage micro-influencer marketing and more inclusively embrace an age-diverse audience, particularly in the communication of health and wellbeing messages.

Whilst studies have been conducted to understand the benefits of micro-influencer marketing (Alampi, 2019) and platform preferences in a general sense (Arora et al., 2018; Shane-Simpson et al., 2018), very limited research has been conducted to determine the social media platform, social media message format, and social media message type preferences of age-diverse audiences when consuming health and wellbeing messages shared by micro-influencers. Therefore, the aim of this study is to examine the social media practices of an age-diverse audience and identify the message strategies of health and wellbeing-focused micro-influencers that are preferred by age-diverse audiences. For the purposes of this study, message strategies include social media platform, message format, and message type (Leung et al., 2017; Shahbaznezhad et al., 2020).

Media richness theory (Daft & Lengel, 1983) and the influencer marketing literature (De Veirman et al., 2017; Hudders et al., 2020) have underpinned this study which investigates social media message strategies preferred by age-diverse audiences when consuming health and wellbeing messages shared by micro-influencers. Data was collected via an online survey comprised of seven sections which examined the demographics of the respondents, their social media practices generally, their social media practices in relation to micro-

influencers, and their message strategy (social media platform, message format, and message type) preferences. Message strategy preferences were determined through a full factorial design discrete choice experiment with 12 choice sets, each comprised of 2 attributes: message format, consisting of 3 levels; and message type, which consisted of 4 levels. There were 375 participants in the total sample (aged 18–78), with 221 participants completing the discrete choice experiment. Participants were recruited through a range of face-to-face and online strategies, including via micro-influencers, social media groups, the researcher's community and professional networks, and local community groups. Data analyses included descriptive statistics, cross-tabulations and chi-square tests, in addition to binary logistic regression to analyse the discrete choice data.

The results revealed significant differences between age categories in relation to their *social media practices*, *social media platform preferences* and *message type preferences*. Further, a media-rich health and wellbeing message format (for example, video), is more likely to appeal to age-diverse audiences when shared by micro-influencers. Interestingly, all age categories considered themselves active social media users, with the Baby Boomers/Post War age category most preferring social networks, such as Facebook, to view micro-influencer messages, whilst Gen Z, Millennials and Gen X prefer media sharing networks such as Instagram.

The overall findings from this study have important implications for both theory and practice. Micro-influencers in the health and wellbeing area, and those who utilise micro-influencer marketing, can draw on the results to inform message strategies and more closely align with the social media practices and information needs and preferences of age-diverse audiences.

While this research is a step toward understanding how to tailor micro-influencer marketing strategies that are more inclusive with regard to age-diverse audiences, it also provides a basis for future research to further address age-diverse audiences and their social media practices, both generally and in relation to influencers and micro-influencers, to ensure that digital and social media marketing approaches are informed by the age-diverse audiences they are wanting to reach.

Declaration

I declare that this thesis presents work carried out by myself and does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university; to the best of my knowledge it does not contain any materials previously published or written by another person except where due reference is made in the text; and all substantive contributions by others to the work presented, including jointly authored publications, is clearly acknowledged.

This thesis received support from an Australian Government Research Training Program Scholarship.



Victoria Taddeo

June 2023

Chapter One: Introduction and Thesis Overview

The first chapter of this thesis provides the background context, summarises the main aim and states the research questions. The research methodology and design are then discussed, followed by a summary of the key findings. The chapter concludes with an overview of the thesis structure.

1.1. Research Context

Significant advances and investment in technology and digital infrastructure over the past two decades has led to a considerable global uptake of digital and online platforms (Plantin & Punathambekar, 2019), particularly for the purposes of digital marketing (Appel et al., 2020). Digital marketing has created new avenues for brands to advertise, reach, and communicate with target customers (Wright et al., 2010) and more diverse audiences, beyond the traditional media outlets such as television, newspapers and magazines. Whilst this type of marketing takes various forms, such as search engine optimisation, search engine marketing, and content marketing (Kingsnorth, 2019), many brands use social media to market and promote their products and services, communicate with their customers, build a loyal clientele, and build brand equity and brand image (Bruhn et al., 2012; Saravanakumar & SuganthaLakshmi, 2012). A digital marketing approach can involve employing the services of digital influencers, including micro-influencers, to be the marketing intermediary between their brand and consumers (De Veirman et al., 2017). A social media marketing strategy is the message strategy implemented to communicate, reach, and engage an audience. This includes the social media platform, message format (for example, picture), and message type (for example, informative) (Shahbaznezhad et al., 2021).

On the other hand, social media platforms can provide consumers with greater control over when, where, and how they consume their media (Adeola et al., 2020) and interact with marketing communications (Hamilton et al., 2016). A relatively new approach for brands to communicate with consumers and potential customers is influencer marketing (De Veirman et al., 2017).

Digital influencers are typically people who have built a significant online presence and following, or social network of followers (De Veirman et al., 2017) and who have the potential to influence the decision-making of their followers, specifically their consumer behaviours. Within the broad category of digital influencers, micro-influencers can be differentiated in their reach and presence online and their engagement characteristics. Typically, micro-influencers provide opportunities for intimate online engagement and communication with followers (Gómez, 2019; Hatton, 2018) and will have a follower count within the four- or five-digit range (between 1,000 and just under 100,000 followers) (Alassani & Göretz, 2019).

Focusing specifically on influencer attributes, micro-influencers are characterised as being credible topic experts who engage and interact with their followers on social media (Alassani & Göretz, 2019) on a much more intimate level than influencers with larger followings (also known as macro-influencers), as they often are classified as 'normal people' and not 'celebrities' (Olsen & Sandholmen, 2019; Schouten et al., 2020). The content created and messages shared by micro-influencers are often perceived by audiences to be more authentic than the content and messages of macro-influencers because they are more relatable and can engage and connect through reciprocal communication (Alampi, 2019; Guzmán et al., 2020).

The authentic relationship between micro-influencers and their followers provides brands that collaborate with them an opportunity to benefit from the relationships and realise improved outcomes, particularly in relation to engagement and sales metrics (Britt et al., 2020). A micro-influencer marketing strategy further enables brands to more intimately connect with audiences, and to have a greater influence on their purchasing decisions (Adeola et al., 2020). Additionally, with a smaller number of followers, micro-influencers are more likely to have an intimate understanding and appreciation of the profiles, demographics and needs of their followers as they are often considered representatives of the target audience (Alampi, 2019). Evidence has shown that the benefits of micro-influencers can, in many instances, rate higher than those with significantly more followers, including a higher engagement rate (Britt et al., 2020).

In the health and wellbeing sector in particular, the implementation of a social media and an influencer marketing strategy has resulted in positive outcomes for organisations, and has been found to play a vital role in promoting and communicating public health topics (Byrne et al., 2017; Mehmet et al., 2020). As seen throughout the COVID-19 pandemic, there are instances where it is crucial for the public to have continuous access to accurate information. Social media, including the use of influencer marketing (Gupta et al., 2021; Pöyry et al., 2022), provides public health organisations with an avenue to provide this constant information, especially as a large portion of the global population are using social media (Bezuidenhout, 2021; Kemp, 2021b).

Statistics show that more than half the global population, that is, 4.2 billion people, use social media (Kemp, 2021b). Although social media users are typically young (Vogels, 2019), increasing accessibility and integration of technologies has resulted in a wider, more diverse, age demographic engaging and communicating online (Pew Research Center, 2019). In response to an ageing global population, particularly in Australia (Fulmer et al., 2020; Office for Ageing Well, 2019), age-friendly considerations are a priority in policy initiatives. In South Australia, the Office for Ageing Well (2019), which sits within the Department for Health and Wellbeing, has identified digital inclusion as one of the three action themes to enable people in the community to age well. The Office for Ageing Well (2019) posits that an age-friendly community is defined as one that supports and contributes to people ageing well. As such, the Office aims to support initiatives that help make technology more accessible to older people, enabling them with opportunities to develop skills and the confidence to interact and connect through digital technology (Office for Ageing Well, 2019). From an industry and commercial perspective, the ageing population forms a considerable part of the consumer market (Arensberg, 2018); thus, we need to better understand the online and, in particular, the social media practices and preferences of age-diverse audiences. Building an understanding of the practices of an age-diverse audience can inform the way brands and commercial businesses innovate, tailor and market products and services to an age-diverse population (Arensberg, 2018), particularly when using digital marketing.

More than ever before, establishing a relationship with a customer and audience base is a key consideration for brands and businesses. Brands and businesses need to be able to

quickly adapt, especially in response to the global COVID-19 pandemic and the changing needs of their customers and audiences (Seetharaman, 2020). Shah et al. (2019) posit that brands should focus on establishing relationships with their customers via social media because it can have a direct impact on the purchase intentions and behaviours of customers as peer-to-peer information is considered more credible than communications and messages created and shared by the brand itself.

However, an important consideration for micro-influencers when building a relationship with an audience and when planning approaches to engage and communicate, is what message strategies are preferred by their audience. Previous studies have explored age-based preferences in relation to message sharing and social media and have found differences in social media platform preferences (YPulse, 2020), the language used (Kuerbis et al., 2017; Muench et al., 2014), and message format preferences (An, 2017). This suggests it also is important for brands and micro-influencers to consider that audiences of different ages may prefer different social media platforms, message formats, and message types.

As the older population are becoming increasingly more active on social media, this presents an opportunity for micro-influencers to tap into this market which can result in follower growth and increased influence. For micro-influencers in the health and wellbeing sector, which has continued to grow online in recent years, messages may not necessarily be restricted to narrow demographics or follower segmentation. This means that for micro-influencers who have a health and wellbeing focus, the topic of their message can have broad audience appeal and could be tailored and shared with audiences from different age categories. As suggested by the media richness theory, when media is aligned to users' information needs, communication effectiveness can be improved (Daft & Lengel, 1983).

Limited research has been done, however, to understand how message strategy preferences vary among diverse age audiences. Therefore, understanding the message strategy preferences of diverse age audiences can provide brands, and micro-influencers specifically, with the information needed to create and share messages that are preferred by their audience.

In acknowledging:

- the increasing ageing population, and identified policy priorities to support ageing well
- the increase in digital communication adaption and consumption by a more diverse, including an older, age audience
- the potential for the current digital age to favour those who have grown up with digital literacy
- the need to better understand the social media practices and message strategy preferences of age-diverse audiences, and
- the potential for micro-influencers to more intimately connect with and share tailored health and wellbeing messages to age-diverse audiences to maximise reach and impact of messages

this research will examine how 'age-friendly' translates to online social media communication and messaging related to health and wellbeing messages shared by micro-influencers. This research first investigates the social media practices of age-diverse audiences, and second, the social media message strategy preferences of age-diverse audiences when viewing health and wellbeing messages shared by micro-influencers on social media.

1.2. Research Aim and Questions

The increased uptake of micro-influencers as a marketing strategy and with age demographics growing online, there is an imperative to rethink the opportunities for leveraging micro-influencer marketing communication to be more inclusive and embrace a broader and age-diverse audience demographic, particularly in the communication of health and wellbeing messages.

Therefore, the overarching aim of this research is to examine the social media practices of an age-diverse audience and identify the message strategies of health and wellbeing-focused micro-influencers that are preferred by age-diverse audiences. For the purposes of this study, message strategies include social media platform, message format, and message

type. In order to address this research aim, this thesis will answer the following research questions:

1) How do social media practices, generally and in relation to micro-influencers, vary among age-diverse audiences?
2) What social media message strategies do audiences of health and wellbeing micro-influencers prefer?
3) How do the audiences' preferences for message strategies vary based on social media platforms and among age-diverse audiences?

1.3. Methodology

To address the research questions and examine the micro-influencer message strategies most preferred by age-diverse audiences, a cross-sectional research design was employed. This research design was considered appropriate as it allowed the associations and relationships between variables to be identified (Mann, 2003) and is useful when investigating the role of moderating variables (Spector, 2019), which, in the context of this study, include 'age' and 'social media platform'.

A cross-sectional online survey incorporated a range of questions to examine the social media practices of an age-diverse audience. The main element of the survey – a discrete choice experiment – helped determine the social media platform and message preferences of an age-diverse audience. The discrete choice experiment elicits study participants' preferences by presenting them with real-life scenarios and asking for choice responses (Louviere et al., 2000). The design of the experiment included attributes and levels which make up the elements of each choice set. Two attributes were included – message format and message type – as they are the key elements that form a message strategy (Leung et al., 2017; Shahbaznezhad et al., 2020). Message format consisted of 3 levels: picture, video, and text. Message type consisted of 4 levels: informative, promotional, interactive, and emotional and relatable. The literature review informed the selection of these attributes and levels. A full factorial design was used in the survey, which consisted of 12 choice sets, each choice set having 2 message strategy options for participants to select as their preference.

Data was analysed by age categories (excluding those under 18) (Table 5), using the generation categorisation guidelines of Beresford Research (2022). However, two changes were made in order to draw meaningful conclusions from the results. First, the Baby Boomers generation was not separated into two (often separated due to the large cohort), and second, Baby Boomers and Post War were combined due to the small number of Post War respondents.

Four strategies were implemented to recruit participants for the study, namely, through micro-influencers on social media; social media groups, for example, local community groups on Facebook; through the researcher's community and professional networks; and face-to-face with local community groups.

The total sample was 375 participants; however, only 221 participants completed the discrete choice experiment and were included in the associated analysis. The study sample included participants aged from 18 to 78 years (M = 37.26, SD = 14.897), with all age generations represented.

1.4. Key Findings

Findings revealed that participants across all age categories, that is, Gen Z, Millennials, Gen X and Baby Boomers/Post War, considered themselves active social media users. Further, when examining social media message strategy preferences, in the context of messages shared by micro-influencers, the video message format, which has a high level of media richness, was more likely to appeal to all age categories.

However, there were some distinct differences between age categories in relation to specific social media practices, social media platform preferences, and message type preferences. For example, Baby Boomers/Post War participants preferred *social networks*, such as Facebook, to view micro-influencer messages, whilst Gen Z, Millennials and Gen X preferred *media sharing networks*, such as Instagram.

When examining if micro-influencer message strategy preferences vary by age category and social media platform preference, the discrete choice experiment revealed that, in relation to message type, both age category and social media platform are important considerations for micro-influencers when sharing health and wellbeing messages. For example, Baby

Boomers/Post War age category preferred *informative* messages significantly more than the benchmark Gen Z age category. This finding is novel, as there is a dearth of literature which has focused on older audiences and social media and message type preferences, and particularly important given older age categories are increasingly active online (Guner & Acarturk, 2020).

1.5. Thesis Structure

Following this introduction chapter, Chapter Two provides a literature review with six main sections. The review begins with a critique of the literature at the broad level, specifically, social media for marketing. Influencers, micro-influencers and influencer marketing will then be discussed, followed by social media user demographics and age-diverse audiences. The fourth section will discuss the theory underpinning this research, namely, the media richness theory. The fifth section reviews the literature on social media message strategies, including social media platforms, message formats, and message types. Lastly, the literature on social media message strategy preferences of social media users will be critiqued.

Chapter Three describes the research design and method used and includes sections on the survey design, the approach underpinning discrete choice experiments, the steps undertaken for the discrete choice experiment, the sampling and recruitment strategies, the ethical considerations of the study, the sample demographics, and data analysis techniques.

Chapter Four presents the results of the study and answers the research questions. Frequencies, cross-tabulations and chi-square statistics are detailed to provide insight into the social media practices of the sample. This is followed by the results of the binary logistic regression which used the discrete choice experiment data to determine the preferences of an age-diverse audience in relation to micro-influencer message strategies.

Chapter Five will discuss the results detailed in Chapter Four, how they answer the research questions and relate to existing literature. This chapter, and the thesis, will conclude with the theoretical contributions and industry and social implications, the strengths and limitations of the study, and considerations for future research.

Chapter Two: Literature Review

The following literature review is organised under six macro level headings, namely, 1) the rise of social media for marketing, 2) influencer marketing, influencers, and micro-influencers, 3) social media users, 4) theoretical underpinnings: media richness theory, 5) social media message strategies, and 6) social media message strategy preferences of social media users. The first section will operationalise the concept of social media and review its role as a marketing channel. The second section will delve into the influencer marketing strategy and the concept of influencers and micro-influencers. The third section will examine user demographics of social media, focusing on use by age-diverse audiences. The fourth section will discuss the theoretical underpinnings of this research, namely, the media richness theory. The fifth section will review social media message strategies and will include sub-sections on social media platforms, social media message formats, and the different types of messages used to convey a message. Lastly, audience preferences for social media message strategies will be discussed.

2.1. The Rise of Social Media for Marketing

2.1.1. Defining Social Media

Since it was first discussed in the literature in 1994, social media has been defined differently by various scholars (Aichner et al., 2020). Pre-2010, social media was frequently referred to as 'social network sites' or 'virtual communities' (Aichner et al., 2020). A common theme amongst definitions during this period was that social media connects people and provides users with a platform to interact. For example, Wellman et al. (1996) defined social media as 'when computer networks link people as well as machines, they become social networks, which we call computer-supported social networks'. Similarly, Marwick (2005) proposed that 'social networking sites are designed specifically to facilitate user interaction for a variety of goals, mainly dating, business networking, and promotion'.

Post-2010, Aichner et al. (2020) found that the focus of most definitions centred on social media as platforms for 'creating and sharing user-generated content' (Aichner et al., 2020).

For example, a commonly referenced definition by Kaplan and Haenlein (2010) states that 'social media is a group of Internet-based applications that builds on the ideological and technological foundations of Web 2.0, and that allows the creation and exchange of user-generated content'. Where social media was once a 'digital place' (Appel et al., 2020) or 'computer-supported social network' (Wellman et al., 1996) that linked people, it is now considered within much broader terms of reference, particularly given the growing number and variety of social media platforms and their features.

In this research and drawing from scholars in the field (Appel et al., 2020; Cheung et al., 2020; Kaplan & Haenlein, 2010; Li et al., 2020; Silva et al., 2020), social media has been defined as follows, *social media provides a diverse set of users including, individuals; firms; institutions; and organisations, a platform to interact and exchange information and user-generated content, including, a digital marketing channel for marketers to advertise and communicate with their consumers*.

2.1.2. Social Media as an Avenue for Marketing

The appeal of social media as an avenue for marketing has been the result of a number of factors, including societal and technological evolution. As consumer reliance on bricks-and-mortar operations and traditional communication channels has declined (Masuda et al., 2022) and the global uptake and activity on social media has increased (We Are Social, 2022b), businesses have been forced to consider alternative and innovative marketing strategies to retain and increase their share of the market (Masuda et al., 2022; Naylor et al., 2012; Schultz and Peltier, 2012). Social media platforms provide brands with greater potential to reach and engage with consumers, whilst the increase in social media users has provided brands with ideal conditions to leverage the platforms for social media marketing (Appel et al., 2020; Gao et al., 2018; Li et al., 2020). Fundamental to the success of social media marketing is the engagement with consumers online, specifically, building and maintaining customer relationships and relationship equity (Cheung et al., 2020; Kannan and Li, 2017; Masuda et al., 2022). When a brand carefully considers customers' motivations for brand-related social media use and then executes purposeful engagement strategies to connect and interact with their consumers, they can achieve desirable marketing outcomes and strategic means (Cheung et al., 2020; Li et al., 2020; Liu et al., 2021).

Tafheem et al. (2022) posits that there has been a shift in marketing practices from a product-centric to a customer-centric position. Nowadays, the key focus for brands is not only the products and services they offer, but also the value they can create and the relationships they can build with consumers and potential customers (Tafheem et al., 2022). Whilst there are competing distractions for consumers' attention online, relationships between consumers and a brand can be strengthened by the interactivity and connection between the two groups in an online setting (Qin, 2020). Vinerean (2017) states that increased social media opportunities to create and share different types of content can increase consumers' engagement and interaction. This suggests that social media can offer an ideal platform for brands to communicate with consumers (Coulter & Roggeveen, 2012).

There are, however, a number of considerations when utilising the platform for digital marketing. Cao et al. (2021) asserts that it is crucial for digital marketing companies to understand consumer engagement from the consumer perspective, specifically, the motivators of consumers social media activity. This knowledge can then assist brands to curate their digital marketing strategy to actively engage customers, which can contribute to maintaining customer loyalty and attracting new customers. As the depth of consumer engagement and reach varies on different social media platforms (Cao et al., 2021; Guidry et al., 2017; Khan, 2017; Wang et al., 2017), it is important for brands to create and share different types of messages not only on one social media platform but across various platforms (Vinerean, 2017). This encourages a high level of consumer interaction and engagement with brands and can assist in the development of a more profound and intimate relationship between the brand and the consumer (Vinerean, 2017). In acknowledging that there are many factors that can impact motivations for, and the nature of, consumer engagement and customer relationships, digital marketers and brands need to understand the attributes of social media, including media richness, to implement a social media marketing strategy that achieves their desired marketing outcomes. Media richness theory (Daft & Lengel, 1983) is a key concept that focuses on the effectiveness of communication when sharing information and the importance of aligning the media used to communicate with the information needs of users/audiences. This theory will be discussed further in section 2.4.

The literature highlights the important relationship between social media marketing and brand metrics (Ebrahim, 2020; Godey et al., 2016; Sanny et al., 2020; Zollo et al., 2020), suggesting that engaging and communicating with consumers through social media marketing positively impacts brand metrics (Cheung et al., 2020) and can assist brands to achieve their marketing, specifically their digital and social media marketing, objectives. For example, Sanny et al. (2020) conducted a quantitative survey of 203 males who had been exposed to social media skincare advertisements and found that social media marketing positively impacted brand trust and brand image. Similarly, a survey study by Ebrahim (2020) of 287 social media users revealed that social media marketing had positive consequences for brands as it can enhance brand loyalty, which are the positive attitudes of a consumer and their likelihood to rebuy from a brand, however, not necessarily brand equity, which is a consumer's perception and social value of a brand. It is important also to note that brand trust was the mediating factor in the relationship between social media marketing and both brand equity and brand loyalty and may be an important consideration when utilising social media marketing strategies. Godey et al. (2016) support Ebrahim's (2020) findings with their results showing significant positive effects of social media marketing efforts on brand loyalty, along with positive effects on brand preferences. Zollo et al. (2020) specifically examined social media marketing effects on brand equity and, in contrast to Ebrahim's (2020) findings, found that social media marketing activities can have positive effects on brand equity, especially if consumers have a positive digital experience with the brand and obtain consumer benefits such as social, cognitive or personal benefits.

2.1.3. Social Media Marketing for Health and Wellbeing Messages

The integration and advancement of technology in society has resulted in an abundance of health communication- and promotion-related social media websites that can be accessed by the public (Stellefson et al., 2020). This has prompted considerable research investigating the role of social media in the context of health and wellbeing messages. Although the use of social media to disseminate health and wellbeing-related messages raises some concerns regarding the spread of misinformation (Bezuidenhout, 2021; Stellefson et al., 2020), it can also result in many positive social outcomes, for example, increased access to health-enhancing support and resources (Mehmet et al., 2020). As social media can provide organisations with the platform to target and reach diverse audiences, it is recognised as a

valuable tool to communicate health and wellbeing messages (Heldman et al., 2013; Mukti and Putri, 2021). As a tool, social media platforms can be used to engage audiences (Kostygina et al., 2020; Pedersen et al., 2020; Rus & Cameron, 2016), educate audiences (Lazard, 2021), promote practices, products or services (Lyson et al., 2019; O'Reilly et al., 2019), and raise awareness (Latha et al., 2020) about health and wellbeing-related topics.

It is evident in the literature that social media has been successful in communicating and promoting health messages to audiences. For example, Pedersen et al. (2020) found that by implementing the 'heart-brain communication' method, which combines facts and emotions in its messaging, a social media campaign addressing hesitancy of the Human Papillomavirus (HPV) vaccination was successful in increasing engagement online and the circulation of positive comments related to the vaccine. Also, regarding HPV and cervical cancer prevention, Lyson et al. (2019) discovered that awareness about HPV can be increased through tailored health messages. More recently, Olum and Bongomin (2020) found that, regarding the usefulness of social media to share COVID-19 public health campaigns in Uganda, social media, in addition to other media, was a useful tool to host reliable COVID-19 information and share research and guidelines related to the pandemic. These studies indicate that spreading tailored public health messages on social media can be effective in raising awareness of health-related information and messages (Lyson et al., 2019). Social media has also been used as a tool to educate the public about health and wellbeing topics and has been found to increase knowledge amongst audiences (Lazard, 2021; Thackeray et al., 2012). Bezuidenhout (2021) suggests that, with the substantial number of people using social media, public health organisations should take advantage of social media platforms to market health promotion campaigns, especially when there are recent and ongoing public health concerns such as COVID-19 and people need constant access to accurate information.

Although there is limited research identifying what social media messaging strategies can be used to convey health and wellbeing-related messages (Pagoto et al., 2019), the implementation of an influencer marketing strategy and use of digital influencers has been identified as one way that social media can be used to disseminate health and wellbeing-related messages (Byrne et al., 2017; Lim et al., 2022; Looi et al., 2022).

2.2. Influencer Marketing, Digital Influencers, and Micro-influencers

The following sections begin with a discussion on influencer marketing and digital influencers more generally before delving into micro-influencers specifically, as they are the sub-category of digital influencers focused on in this study.

2.2.1. Influencer Marketing and Digital Influencers

The rise of social media and the various diverse social media platforms available has provided brands in a range of industries, such as health and wellbeing, with a new avenue for communicating with consumers. These new social media platforms, which enable and facilitate communication between brands and consumers, have further contributed to a growth in digital and social media marketing. Influencer marketing, defined as 'a marketing strategy that uses the influence of key individuals or opinion leaders to drive consumers' brand awareness and/or their purchase decisions' (Lou & Yuan, 2019), is one social media marketing strategy which has experienced considerable growth, with 75% of marketers, as of 2015, implementing an influencer marketing strategy in various industries (De Veirman et al., 2017). The popularity of influencer marketing has been discussed widely in the literature. For example, Fink et al. (2020), and Kolo and Haumer (2018) discuss the viability of influencer marketing as a sustainable method of advertising over long periods of time and the impact that influencer marketing can have on building a brand and brand metrics. These findings are supported by Chopra et al. (2020), Ki and Kim (2019), and Lou and Yuan (2019) whose studies also have shown that influencer marketing can support positive outcomes for brand metrics.

A number of studies have been conducted to understand the role of influencer marketing and influencers in public health. Byrne et al. (2017) conducted a study with 232 participants which revealed that influencers can play a fundamental role in public health promotion, especially in motivating audiences to adopt a healthier diet. Similarly, Kostygina et al. (2020) investigated the impact of content and source features of Twitter messages on popularity, support, and reach of Truth® (anti-tobacco) campaigns. Findings revealed that by using digital influencers, campaigns can achieve greater reach to their audience and improve

interest and engagement. Nobles et al. (2020) support these findings as the implications of their study suggest that using individuals or organisations who are influential and trusted in the community can be a valuable method to deliver messages to the public, especially in sharing messages regarding the benefits of physical activity. Collectively, these findings highlight the benefit of incorporating an influencer marketing strategy for health and wellbeing-related campaigns.

The appeal and advantages of influencer marketing have led to changes in the way marketers and brands communicate and engage with consumers and their customers (George et al., 2021; Trivedi, 2018). Core to influencer marketing and the success of the strategy are the digital influencers. The idea that 'influencers provide brands with an avenue of communication to their audience' is a common concept in the marketing literature (Fink et al., 2020; Kolo & Haumer, 2018). Brands are increasingly acknowledging that influencers can provide a marketing strategy and edge which can have considerable impact on their brand (Fink et al., 2020; Kolo & Haumer, 2018). The reach and impact that digital influencers can achieve on social media presents valuable opportunities and has led many brands to incorporate an influencer marketing approach and employ digital influencers as part of their digital marketing strategy (De Veirman et al., 2017; George et al., 2021; Lou & Yuan, 2019).

Digital influencers are individuals who have built a strong presence on social media by growing their audience and are considered to be a trusted source by their followers (Agostino et al., 2019; Carter, 2016). They are perceived as ordinary, approachable, and authentic, which are characteristics that resonate with followers and are traits that are more likely to result in stronger connections with the social media figure (Chapple & Cownie, 2017; Schouten et al., 2020).

Digital influencers typically embrace two key characteristics: impact and reach (Carter, 2016; Hudders et al., 2020). Reach refers to not only their considerable follower base and their direct reach to them, but also their secondary reach through other influencers and their followers. Carter (2016) suggests that even an influencer with a small number of followers may be highly influential through their reach and still have considerable impact on attitudes and behaviours of followers because they can act as a bridging function between different communities. Impact can be realised in different ways – for example, a positive

impact on consumer decisions, such as purchase intention, is identified as a result of influencer marketing. Kolo and Haumer's (2018) multi-methodological study observed 40 followers of social media influencers. They conducted a content analysis of YouTubers' posts and surveyed 1,000 participants aged 14 to 35 and found that digital influencers have a considerable influence on consumer decisions.

The impact of the influencer also can refer to their role in being an 'opinion leader' and their ability to influence the decision-making and health perceptions or practices of others (Chetioui et al., 2022; Farivar et al., 2021; Hudders et al., 2020; Pöyry et al., 2022). The degree to which digital influencers are perceived as opinion leaders amongst their followers can depend on the characteristics of the influencer's social media account and the personal traits of the influencer themselves. In efforts to identify key antecedents of opinion leadership, Casaló et al. (2018) surveyed 808 followers of a fashion-focused Instagram account and identified that the originality and uniqueness of a digital influencer's account can determine if that influencer is an opinion leader. Similarly, Ki and Kim (2019) surveyed 591 social media users between the ages of 18 and 49 who use Instagram to explore the mechanisms that digital influencers use to persuade consumers to adopt brands. One of the constructs measured was opinion leadership. The study found that the way influencers interact with their audience, their level of expertise in their field, and the information they provide in their content/messages, all affect the followers' attitudes towards the influencer and the extent to which digital influencers are considered opinion leaders (Casaló et al., 2018; Farivar et al., 2021; Ki & Kim, 2019).

The terms 'opinion leader' and 'endorser' are used frequently and interchangeably in the influencer marketing literature and for many years it was common practice for brands to use celebrities as endorsers in their marketing communication and strategy (Erdogan, 1999; Ohanian, 1991). Employing a longitudinal design and surveying 234 members of a Facebook fan community, Fink et al. (2020) discovered that celebrity endorsements (a form of influencer marketing) as a marketing strategy can have a positive impact on the purchase intention of consumers. However, for this method to be effective, the credibility of the celebrity as the endorser must be solid amongst the target audience (Dwivedi et al., 2015; Fink et al., 2020).

Unlike traditional celebrities, digital influencers have already built a strong rapport and relationship with their audience by engaging with them in an open and candid way, and so are considered more credible, trustworthy and authentic (Campbell & Farrell, 2020; Schouten et al., 2020; Trivedi, 2018). This is a considerable advantage for brands implementing an influencer marketing strategy and who use influencers to endorse and promote their brand, product or service, or share important health and wellbeing messages, as the credibility of an endorser, in this case the digital influencer, can impact how effective the advertising or marketing communication is to a brand's target audience (Trivedi, 2018). As such, the impact and reach of digital influencers identify them and their platform as an ideal avenue for brands' marketing communication and public relations (Carter, 2016; Hudders et al., 2020).

As the success of the influencer marketing strategy relies heavily on established relationships between a digital influencer and their followers, it is important to be able to identify and measure attachment between a digital influencer and their followers. Ki et al.'s (2020) survey of 325 American consumers sought to understand what mechanism fosters the attachment between influencers and their followers. Findings revealed that followers perceive influencers as human brands who have a strong attachment with their followers when they fulfill their followers' needs for ideality, relatedness, and competence. The attachment between influencer and follower is what results in positive marketing outcomes for brands that employ an influencer, including, influencing followers to purchase products recommended by them. These findings are supported by Kim and Kim's (2022) study, which also found that the emotional bond and attachment that influencers develop with their followers can prove valuable in achieving marketing objectives. However, as the following of a digital influencer grows, maintaining the relationship on an authentic level and meaningfully connecting with followers can become more problematic. This has resulted in the categorisation of digital influencers based on the number of followers. Micro-influencers, known for their more intimate relationships with their followers, are one such sub-group and the influencer marketing category that this study focuses on.

2.2.2. Micro-influencers as a Marketing Strategy

The literature identifies micro-influencers as having the best combination of engagement and reach (Farivar et al., 2021). The term 'micro-influencer' in the context of social media and influencer marketing is a relatively new concept. A micro-influencer is classified as a digital influencer who has a smaller following than a macro-influencer (Alampi, 2019). There is, however, variation in the literature on what constitutes a micro-influencer, depending on various characteristics, the most prominent being a micro-influencer's follower count.

As the term 'micro-influencer' originated in industry, many papers have drawn on definitions and references of micro-influencers from industry reports and articles written by practitioners. One key study conducted by influencer marketing company Markerly (2015), which has been referenced by multiple academic and industry papers, for example, Alassani and Göretz (2019) and Gómez (2019), identifies micro-influencers as those who have a follower count between 10,000 and 100,000. Alampi (2019) classifies micro-influencers as having between 1,000 and 50,000 followers. Pedroni (2016), Boerman (2020) and Britt et al. (2020) consider micro-influencers to typically have dozens to hundreds (up to 10,000) of followers. Boerman (2020) identifies an additional influencer bracket, 'meso-influencers', which sit between micro- and macro-influencers, and have between 10,000 and one million followers. Acknowledging that there is no broad consensus in the field, this research classifies micro-influencers as digital influencers who have between 10,000 and 100,000 followers, as this is referenced in both industry reports and academic papers and is inclusive of the other classifications of micro-influencers in the literature.

Although micro-influencers have a smaller number of followers compared to macro-influencers or celebrities, they still have a considerable following and audience and, more importantly, a greater capacity to connect and interact with their followers on a more intimate and personal level (Farivar et al., 2021; Olsen & Sandholmen, 2019). A study conducted by Marques et al. (2020) found that, compared to celebrity endorsers, micro-influencers' posts on Instagram received more clicks, comments, and likes (which are considered engagement metrics). This level of interaction and engagement enables micro-influencers to be perceived as more authentic and accessible to their followers, which in turn can result in greater awareness of their needs and interests (Alampi, 2019; Campbell & Farrell, 2020; Trziszka, 2021). This increased level of engagement, communication, reach,

and authenticity increases micro-influencers' persuasive impact and is one of the reasons that brands, including health and wellbeing brands and organisations, have shifted from the traditional social media or 'celebrity endorsement' marketing strategy, to using digital influencers, specifically micro-influencers, to communicate with their target audiences and social media users (Appel et al., 2020; Campbell & Farrell, 2020; Chetioui et al., 2022; Gupta et al., 2021; Hudders et al., 2020; Kim and Kim, 2022). As such, this research focuses specifically on micro-influencer message strategies used on social media platforms and examines the practices of social media users to help ensure that micro-influencer messages are aligned with the information needs of audiences (Daft & Lengel, 1983). The next section reviews the literature on social media users.

2.3. Social Media Users

According to the *Digital 2022 Global Overview Report,* a report published by a partnership between creative agency, *We Are Social*, and social media management platform, *Hootsuite,* more than half of the world's population are using social media. Since 2020, the number of social media users has grown by just under one billion users, to 4.62 billion people globally being active on social media platforms as of January 2022 (We Are Social, 2022b). In Australia, 82.7% of the total population use social media (We Are Social, 2022a). With regard to time spent on social media, statistics show that those aged 16 to 64 years engage with social media for 1 hour and 57 minutes on average per day (We Are Social, 2022a), and in 2021, Australians were mostly using the social media platforms Facebook, YouTube, Facebook Messenger or Instagram (Park et al., 2021).

2.3.1. Social Media User Demographics and Practices of Age-diverse Audiences

Typically, Millennials and younger people have been the first to adopt and use new technology, including social media, as they are considered digital natives (Bolton et al., 2013; Eastman et al., 2021; Vogels, 2019). Although this is still largely true, in recent years there has been a considerable increase in those in an older demographic using and adopting technology and digital platforms for a variety of reasons, including increased confidence and competence in using technology (Kemp, 2020; Pew Research Center, 2019), willingness to learn and use technology (Guner & Acarturk, 2020), and in response to environmental and societal requirements, such as adapting to COVID-19 restrictions (Park et al., 2021; Pew

Research Center, 2019; Vogels, 2019). To understand this technology adoption, Guner and Acarturk (2020) conducted a study to understand the use and acceptance of information and communication technologies of elderly citizens (aged 60 +) when compared with younger adults (aged 18–40). By surveying 232 elderly adults aged 60–96 years and 235 younger adults aged 19–40 years, the researchers found that the usefulness and ease of use of technology have a significant impact on the acceptance of technology across both younger and older adults. Although older adults experienced several barriers and constraints to their uptake of technology, including costs and the need for technology support, it was evident that many seniors were interested in learning and using technology (Guner & Acarturk, 2020).

With technologies becoming increasingly integrated in everyday life, the capacity for an older demographic to have the confidence and skillset to engage with technology to access information and services and communicate and connect with others is essential as part of an age-friendly society (Guner & Acarturk, 2020). To understand the ways in which older adults can access and obtain informal information (knowledge management) through using social media, Dumbrell and Steele (2014) conducted a mixed method study with a sample of 150 adults aged 55 plus. The pre-post study involved participants being taught how to use three social media platforms (Facebook, Twitter, and Skype) over two training sessions. Participants were then given six months to use the platforms. Results revealed that, not only did 77% of participants use social media to find and access information during the six months, but 79.1% indicated that they would continue to use social media after the research trial period ended. As evidenced by this study, the older demographic are embracing and using social media. In order to effectively communicate health and wellbeing messages on social media to this age demographic, it is important to understand their social media practices and message strategy preferences.

To understand which factors underpin the use of social media for older people, Kim et al.'s (2019) quantitative study sought to understand seniors' motivations for using social media network sites in the context of tourism-related activities. The data from 500 respondents revealed the attributes of innovation diffusion (simplicity, benefit, and compatibility) and the attributes of uses and gratifications (informativeness, social interactivity, and playfulness) had a greater effect on providing an authentic experience than site attachment.

Kim et al. (2019) defined site attachment as maintaining user connectiveness to online communities through websites and it is generally considered an important element in increasing user loyalty to social networking sites (Kim et al., 2019). Although a limitation of this study is that the research focused on only tourism-related activities, the need for social media network sites to be simple, beneficial, and compatible for seniors' use can be applicable to marketers, including micro-influencers and those utilising micro-influencer marketing, in multiple and varying industries that use social media to connect with an older demographic. This highlights the importance of understanding social media practices and the message strategy preferences of older age categories in order to align media to their information needs and better connect with them on social media.

The literature also highlights the general benefits older adults can experience as a result of using social media and social networking sites. A study surveying 1,026 adults aged 60 plus years found that older adults who engage in online activities, such as interacting with others through asking questions, have greater social capital, with social capital considered the relationships and resources gained through social networks (Nguyen et al., 2020). Using pre-existing data from a sample of 7,524 participants from the Health and Retirement Study, Zhang et al. (2020) concluded that older adults' increased social support and social contact obtained by frequently communicating on social media was associated with lower levels of loneliness. Despite these potential advantages, the literature suggests older adults are at risk of being excluded from experiencing the benefits associated with access to digital technologies (Gil-Clavel et al., 2020).

With the increase in the older demographics' use of technology, including social media use, and statistics which show the ageing nature of the world's population (Guner & Acarturk, 2020; World Health Organization, 2015), there is a need for age-friendly initiatives which empower members of a society to age well by enhancing their capacity to function optimally (Greenfield et al., 2015). International, national, and local government departments have began to address this concern and provide older people with the opportunity to connect with information and services via digital technologies, including social media platforms (World Health Organization, 2019). Locally, the South Australian Department for Health and Wellbeing, have identified digital inclusion as an action theme to enable people in the community to age well (Office for Ageing Well, 2019). In response to

this priority, programs are being implemented to help increase older people's skills and confidence in using technology (Office for Ageing Well, 2019).

Despite some of the challenges that older adults may face in their adoption and use of technology, the prioritisation of older people's digital skills enables older adults to be well positioned to benefit from opportunities enabled via social networking sites (Nguyen et al., 2020). This benefit is two-fold, in that entities such as micro-influencers and other marketers can capitalise on opportunities to build relationships with seniors; however, in doing so they need to consider message strategies that align with the specific needs of this age group (Office for Ageing Well, 2019; World Health Organization, 2015). By considering the older age demographic and market segment when creating and delivering their social media and marketing messages, digital influencers and brands can provide authentic digital and online marketing experiences to age-diverse audiences. This will help ensure that the messages strategies used on social media by entities like micro-influencers will have greater potential to appeal to age-diverse audiences, which is particularly important when sharing health and wellbeing-related messages.

Given that age-diverse audiences, including an older demographic, are active online (Park et al., 2021; Pew Research Center, 2019; Vogels, 2019), there is an imperative to better understand audiences' preferences for micro-influencer message strategies to help micro-influencers, and those who utilise micro-influencers for their marketing and communications, better tailor health and wellbeing message strategies to align with the information needs of their audience. In addition to the important practical and societal implications which support examining the preferences of age-diverse audiences, media richness theory states that when media is aligned with users'/audiences' information needs, communication can be more effective. Therefore, this study is underpinned by the media richness theory (Daft & Lengel, 1983) and will be discussed in the following section.

2.4. Theoretical Underpinnings: Media Richness Theory

Introduced by Daft and Lengel (1983), the theory of media richness suggests that communication effectiveness can be improved by aligning media with users' information needs. The theory arose as an extension of the information processing theory and was first applied to how information is processed in organisations (Daft & Lengel, 1983). The term

'media' referred to the media used to communicate information. Daft and Lengel (1986) posit that the different variations in communication media can impact the way information is processed by the receiver. This supports the applicability of the media richness theory to research in the field of social media marketing and influencer marketing, as the strategy used to communicate with an audience on social media can impact audience engagement. The media richness theory assists in evaluating whether the medium used facilitates the communication effectiveness of a message (Carlson & Zmud, 1999).

The literature reveals a number of different approaches to classifying media. Daft and Lengel (1986) initially identified five media classifications: 1) face-to-face, 2) telephone, 3) personal documents, for example, letters or memos, 4) impersonal written documents, and 5) numeric documents. Lengel and Daft (1984) identified four elements that distinguish the level of media richness: 1) the ability of the medium to enable rapid feedback, 2) the ability to use several channels to respond to information cues simultaneously, 3) the ability to tailor messages to suit the personal situation of the audience, and 4) variety in the language and symbols used to convey a message. Two additional elements: 5) computer processable memory, and 6) externally recordable and concurrency, were included to address the technology and communication advancements (Lodhia, 2018), such as the introduction of social media.

Since its inception, the media richness theory (Daft & Lengel, 1986) has been applied and expanded by various scholars in both the communication and social media marketing fields (Brunelle, 2009; Cao et al., 2021; Carlson & Zmud, 1999). In the context of social media, one application of media richness focused on the message format, such as video, used by brands in their social media communications (Moran et al., 2019). Moran et al. (2019) proposed that the richness of the format would determine the engagement level of the communication, as a high level of richness is more likely to result in higher engagement. Moran et al. (2019) also highlighted the importance for content shared on social media platforms to represent a high level of media richness in order to increase engagement and visibility within the large volume of content. For example, message formats that involve interactive features or motion activity usually have a high level of media richness and therefore experience a higher level of engagement from audiences (Shahbaznezhad et al., 2021). However, Daft and Lengel (1986) suggested that when communicating content or

messages that are clearly understood by the audience or considered standard information, low media richness also can be effective (Daft & Lengel, 1986). Carlson and Zmud (1999), further suggested that media richness can also refer to the channels used and their potential to deliver messages that communicate rich information. For example, Cao et al. (2021) have classified media richness from the perspective of the digital medium used to communicate a message, namely social media platforms.

As will be discussed in sections 2.5.1 and 2.5.2, the media richness theory has been applied to a social media context to identify which message formats and social media platforms deliver rich media. Although the choice of medium used to deliver a message is typically determined by the attributes of the message and who the audience is (Cao et al., 2021), research has been conducted to understand which message formats and social media platforms have a high level of media richness within the context of the hotel and airline industries (Leung et al., 2017; Shahbaznezhad et al., 2021). However, to date, limited studies have applied the media richness theory to the context of health and wellbeing messages shared by micro-influencers. This represents an important theoretical gap as micro-influencer marketing is increasingly being utilised to share health and wellbeing messages. These messages can differ in what they present or offer to the audience (for example, intangible self-benefit as opposed to a product, service or experience) and so warrant further investigation of the media richness theory and its applicability to this different context. This has important implications, because micro-influencers who better understand the information needs of their audience and who may have high levels of authentic connection and engagement with their audience, may be able to more effectively disseminate messages about health and wellbeing. The media richness theory is further applied in this study to understand whether there are variances in the media and information needs among diverse-age audiences within the context of social media use and activity, and health and wellbeing messages shared by micro-influencers.

The media richness theory highlights the importance of aligning media to users' information needs to ensure that information, or messages, are effectively communicated. When sharing information or messages on social media, the literature highlights three key components. These three components form a social media message strategy and include

social media platform, social media message format, and social media message type. The following section discusses each component.

2.5. Social Media Message Strategies

As discussed, social media provides a platform for individuals and organisations to engage and communicate with their target audiences. However, there are many facets of social media that need to be considered by individuals, like micro-influencers, and those who utilise micro-influencers, in order to create messages which audiences want to consume and engage with. Creating messages that align with the information needs of audiences (Daft & Lengel, 1986) can then positively impact metrics, such as the effectiveness of the message (Kusumasondjaja, 2018), engagement and communication with followers (Cao et al., 2021; Jaakonmäki et al., 2017; Shahbaznezhad et al., 2021), buying and purchase intentions (Adelaar et al., 2003), and brand-related metrics, for example, brand awareness and brand trust (Lou & Yuan, 2019; Nguyen & Nguyen, 2020). Three key aspects of social media message strategies will be discussed in the following section: 1) the social media platforms on which messages can be delivered and consumed, 2) the social media formats used to deliver the message, and 3) the types of social media messages.

2.5.1. Social Media Platforms

In recent years, increase in digital infrastructure has provided the foundation for social media platforms to emerge and evolve (Plantin & Punathambekar, 2019). Types of social media platforms can be divided into various categories, depending on their purpose. Foreman (2017) identified ten types of social media platforms: 1) social networks (e.g., Facebook, Twitter, LinkedIn), 2) media sharing networks (e.g., Instagram, YouTube, TikTok), 3) discussion forums (e.g., Reddit), 4) bookmarking and content curation networks (e.g., Pinterest), 5) consumer review networks (e.g., TripAdvisor), 6) blogging and publishing networks (e.g., WordPress), 7) social shopping networks (e.g., Etsy), 8) interest-based networks (e.g., Goodreads, Houzz), 9) 'sharing economy' networks (e.g., Airbnb, Uber), and 10) anonymous social networks (e.g., Ask.fm).

When focusing on social media platforms for marketing and communication purposes, social networks, such as Facebook and Twitter, and media sharing networks, such as Instagram

and YouTube, are frequently used by brands to engage and communicate with consumers (Cao et al., 2021). According to Cao et al. (2021), the platform on which content and messages are shared can have a considerable impact on the depth of audience engagement. Studies have shown that for digital influencers, the most important social media platforms in 2018 were YouTube, Instagram, and blog-hosting services such as WordPress (Enke & Borchers, 2019). There is consensus in the literature, however, that each social media platform offers different features and attributes (Cao et al., 2021; Shahbaznezhad et al., 2021). Therefore, in order for brands to execute an effective social media marketing strategy, brands need to align the features and functionality of the platform, such as message format options, with their marketing and communication purpose (Cao et al., 2021). A survey study conducted by Voorveld et al. (2018) with 1,346 participants aged 13 years and older, examined consumers' engagement with social media and social media advertising on different social media platform types. Results support Cao et al. (2021) and Shahbaznezhad et al.'s (2021) findings in that consumers had different experiences on each social media platform, given the different features and functionalities of each platform. Additionally, Voorveld et al. (2018) found that consumers also engage with social media advertising differently, depending on the platform. This has implications for brands and highlights the importance of implementing a multi-platform social media approach in which they share the same message across a range of platforms (Shahbaznezhad et al., 2021). Importantly, however, the message strategy should be tweaked to align with the features and functionality of each platform, in order to reach a wider audience (Shahbaznezhad et al., 2021).

Another key consideration for brands is the potential change in the dynamic of the message being delivered depending on the social media platform used (Lodhia, 2018). This suggests that engagement with consumers on social media is highly platform-specific and has implications for the level of consumer engagement (Voorveld et al., 2018), including whether they are passively or actively engaging (Shahbaznezhad et al., 2021). Cao et al.'s (2021) paper, which focuses on the fashion retail industry, drew from the media richness theory (Daft & Lengel, 1986) and discussed how the social media platforms Facebook, Twitter, Instagram, Pinterest, and YouTube all vary regarding the characteristics of the

platform, which in turn determines their richness. For example, because Instagram hosts high-quality visual content, it potentially elicits more intense engagement.

Richness of social media platforms can have considerable impact on brand engagement with consumers as, depending on the platform, they can promote varying social and interactive experiences (Cao et al., 2021; Guidry et al., 2018). Research has shown that consumers are more likely to engage with social media marketing content that is shared on platforms that have a higher level of media richness (Cao et al., 2021). In noting this, however, active social media users choose different platforms to align with their own needs (Chen et al., 2020). Whether the user is satisfied with their chosen platform can influence their subsequent platform choice and usage (Chen et al., 2020).

As influencers rely heavily on a social media platform's algorithm to reach and connect with their audiences, the way in which messages are distributed needs to be considered within the context of the platform being used (Enke & Borchers, 2019). As part of this, it is also important for both influencers and marketers to consider media richness, in order to maximise reach and audience and consumer engagement on social media (Cao et al., 2021). As such, the formats in which messages are delivered on social media platforms also play an important part in how messages are conveyed.

2.5.2. Social Media Message Formats

As discussed above, different social media platforms provide different functionalities and features to its users and so can influence and impact user experience. Message format is an important element that forms part of a social media message strategy. An important consideration when creating messages is that message formats need to align with platform features and functionality and the formats that are available on platforms (Cao et al., 2021).

Message formats have been categorised differently throughout the literature. For example, Huang and Wang (2020, p. 3) classifies message format as narrative versus non-narrative, where narratives are 'messages with a story plot that conveys characters' actions and outcomes' and non-narrative messages are considered 'messages that change attitude primarily through rhetorical reasoning, facts, and statistics'. Chae (2020) classified humour, length of text, and use of hashtags as contributing factors to message formats and identified

emotional or informational appeals as message tone. The aim of a study conducted by Leung et al. (2017) was to develop a typology of social media messages by conducting a content analysis of 1,837 messages from 12 hotel brand Facebook pages. Leung et al. (2017) divided the typology into two categories: message content (discussed in 2.5.3) and message format. The researchers identified four types of message format: word, picture, web link and video. Whilst a limitation of this study is that Facebook was the only social media platform analysed, Facebook does allow for an array of message formats, such as text, photo and video posts, that could be somewhat representative and generalisable to message formats available on other social media platforms, such as Instagram and YouTube.

Shahbaznezhad et al. (2021) explored message format from the perspective of the media richness theory (Daft & Lengel, 1986). This theory posits that by aligning users' information needs to the type of media, communication can be improved and be more effective (Daft & Lengel, 1986). Rich media typically consists of interactive features and motion activity, commonly seen in the format of videos and audio. That is not to say that other message formats, such as still photos or images, are not useful; however, they may be suited to certain audiences and depend on the message topic (Daft & Lengel, 1986) and also tend to result in a different type of engagement behaviour (Moran et al., 2019). In addition to understanding the impact of platform on user engagement as discussed in section 2.5.1., Shahbaznezhad et al. (2021) also investigated if message format can impact user engagement behaviour. The study revealed that where high media richness tends to elicit more active engagement from audiences, in the form of sharing opinions and comments on shared content, low media richness stimulates a more passive engagement, in the form of 'liking' content. Moran et al. (2019) supported these findings, as their study also revealed that messages delivered via rich media formats attract a higher level of engagement than messages that lack media richness.

As content creators, one of the key considerations for digital influencers is to create rich content to share on social media platforms. Although this can take various forms, Enke and Borchers (2019) identified written texts, pictures, and videos as the most important message formats for influencers when disseminating their messages.

Research also shows that message formats can have implications on the outcomes of messages shared and therefore need to be considered by those who use social media to convey messages to an audience (Leung et al., 2017). Păvăloaia et al. (2019) conducted a study analysing two companies in the beverage industry and the reactions of existing or potential customers to two different social media message formats, video and photo, on six different social media platforms. Results indicated that the format of the post does impact how users express their opinions. A main finding of the study indicates a preference for photos and a reluctance towards using videos. The researchers suggested that a reason for this may be the clearer and more concise expression of a message in a photo than in video posts. Audiences are also able to perceive and understand messages in photos faster, which could also contribute to this finding. Specific to health communication, Rus and Cameron (2016) sought to understand the message features that predict engagement on Facebook pages that are related to the topic of diabetes. They found that although the use of images is beneficial in attracting attention, engaging audiences briefly and encouraging the transmission of the message (i.e., attracting likes and increasing shares), engagement can decrease if the images and tone of the message are negative. The use of sharing external links was associated with lower audience engagement. This is potentially a result of the implementation of an extra step to access the message (Rus & Cameron, 2016). Although a message in the external link may result in high engagement, it is suggested that audiences prefer messages that are presented concisely on one platform (Rus & Cameron, 2016).

Given that the communication and outcomes of messages with different message types (to be discussed in section 2.5.3) do vary considerably depending on the social media platform and the message format (Shahbaznezhad et al., 2021), the following section will explore message types.

2.5.3. Social Media Message Types

The third consideration of a social media message strategy is the type of message. Similar to social media platform and message format, message type, also described as content type or message content by some scholars, can also influence how messages are conveyed to an audience. There is some crossover between message format and message type in the literature, and thus defining ‘message type’ can pose some challenges. However, message

type typically refers to the style and structure of the message being delivered via a message format on a social media platform (Leung et al., 2017; Shahbaznezhad et al., 2021). Many studies have been conducted to understand message types which are used by individuals and brands to communicate with their audience.

In Leung et al.'s (2017) typology of social media messages, their second classification in the typology (first classification being message format, as discussed in section 2.5.2.) includes six different types of message content: product, promotion, reward, brand, information, and involvement. Their study found that messages that fit within the categories of product, brand, and involvement were more effective message types than reward, information, and promotion. As mentioned in section 2.5.2., Chae (2020) identified emotional or informational appeals as message tone; however, both these attributes fit within both Shahbaznezhad et al.'s (2021) and Leung et al.'s (2017) typologies as content type or message content, and so can be classified as a part of message type. Tafesse and Wien (2018) draw on pre-existing advertising message typologies to develop a typology of branded social media content. The typology consists of informational (functional, and educational), transformational (emotional, brand resonance, experiential, and social-cause related), and interactional (current events, personal, brand community, and customer relation) message types.

Shahbaznezhad et al. (2021) draw some parallels with Leung et al.'s (2017) typology as they identified three classifications of content type in their paper: 1) rational, which consists of content that provides audiences with information and resources, and is educational, functional, or a current event, 2) emotional, and 3) transactional, which is typically of a remunerative nature and consists of brand resonance or sales promotions. The study by Shahbaznezhad et al. (2021) investigated how social media message format and platform alters the effects of the three types of content or messages (rational, emotional, and transactional) on audiences' active and passive engagement behaviour. Their analysis of 1,038 posts, with 1,336,741 likes, and 95,996 comments of two international airline firms with a high level of activity on Facebook and Instagram revealed that there are significant variations in the level of engagement with rational, emotional, and transactional content, depending on the format of the content and the platform on which the content is delivered. For example, when sharing rational content, marketers should consider that this content

type can be sensitive to both format and platform type when measuring audience engagement (Shahbaznezhad et al., 2021). Emotional content, on the other hand, was found to be best suited to rich forms of media, such as video, as it can convey a greater level of emotion through characteristics such as movement and music and will result in a higher level of audience engagement (Shahbaznezhad et al., 2021).

Kim et al. (2021) approach content type as either being objective or subjective. Although this perspective varies from how the scholars above have categorised content or message type, there are similarities when looking at the characteristics of each content type. For example, objective content typically consists of promotional messages and can include factual information and/or provide numeric values about product attributes. Subjective content typically consists of experiential messages that include evaluative and emotional opinions or impressions about products. Both promotional and experiential content types are commonly identified as content or message types by other scholars in the literature.

Digital influencer content, on social media specifically, can also be categorised into two types: sponsored or branded content and user-generated content. Generally, user-generated content is 'material that a platform sources from its own end users' (Luca, 2015) which, in the context of social media, refers to the users of social media platforms. Conversely, sponsored or branded content consists of advertising or commercial content (De Veirman & Hudders, 2020). When influencers and micro-influencers are involved in the production of sponsored content, it is usually in the form of a product or service review, or an endorsement of a brand, which they post on their social media platforms and receive some form of compensation from the brand sponsor (Evans et al., 2017; Stubb & Colliander, 2019). To understand perceptions of sponsored content, Coco and Eckert (2020) conducted 15 in-depth interviews with women to explore their perceptions of sponsored content posted by digital influencers. The study revealed that there are mixed opinions of influencer-sponsored content with the main emotional responses from followers including disgust, annoyance, distrust, and support. However, the concept of influencer authenticity has a considerable role in the attitudes of followers when exposed to an influencer's sponsored content (Coco & Eckert, 2020).

Four main categories of message type can be identified across the literature: rational, transactional, interactional, and transformational. Rational messages include messages that discuss current events, highlight the functional attributes of a product or service, or provide information and resources to educate consumers about a brand, product and/or service (Chae, 2020; Leung et al., 2021; Shahbaznezhad et al., 2021; Tafesse & Wien, 2018). Transactional messages include messages that are promotional or sales driven, discuss rewards or are of a remunerative nature (Leung et al., 2021; Kim et al., 2021; Shahbaznezhad et al., 2021). Interactional messages are more personal in nature and seek to involve, and interact with, audiences in order to build relationships with them (Leung et al., 2021; Tafesse & Wien, 2018). Current events are also a form of an interactional message as they are considered an active talking point (Tafesse & Wien, 2018). Transformational messages consist of messages that are emotional or social-cause related and that marry an experience and identity of a brand, product or service with the positive psychological characteristics of the audience (Chae, 2020; Kim et al., 2021; Shahbaznezhad et al., 2021; Tafesse & Wien, 2018). Table 1 provides a summary of each message type.

Table 1: Categories of message type

Rational (Informative)	Transactional (Promotional)	Interactional (Interactive)	Transformational (Emotional or Relatable)
Informational (Chae, 2020; Shahbaznezhad et al., 2021; Leung et al., 2017) Resources (Shahbaznezhad et al., 2021) Educational (Shahbaznezhad et al., 2021; Tafesse & Wien, 2018) Functional (Shahbaznezhad et al., 2021; Tafesse & Wien, 2018) Current events (Shahbaznezhad et al., 2021) Product (Leung et al., 2017) Brand (Leung et al., 2017)	Remunerative nature (Leung et al., 2017; Shahbaznezhad et al., 2021) Promotion (Kim et al., 2021; Leung et al., 2017; Shahbaznezhad et al., 2021)	Involvement (Leung et al., 2017) Current events (Tafesse & Wien, 2018) Personal (Tafesse & Wien, 2018) Brand community (Tafesse & Wien, 2018) Customer relation (Tafesse & Wien, 2018)	Emotional (Chae, 2020; Shahbaznezhad et al., 2021; Tafesse & Wien, 2018) Brand resonance (Tafesse & Wien, 2018) Experiential (Kim et al., 2021; Tafesse & Wien, 2018) Social-cause related (Tafesse & Wien, 2018)

Acknowledging the many and varied social media strategy options that can be utilised by micro-influencers to deliver messages on social media, the following section discusses preferences of audiences/social media users in relation to social media platform, message format, and message type.

2.6. Social Media Message Strategy Preferences of Social Media Users

This section will highlight the existing literature on social media users' preferences of social media message strategies, including social media platform, social media message format, and social media message type.

2.6.1. Preferences of Social Media Platform

Regarding social media platforms, studies in both the scholarly and grey literature have been conducted to determine user preferences. When examining the social media platforms

usage statistics, the We Are Social (2022b) report states that, as of January 2022, globally, Facebook is the most used social media platform in the world. This is then followed by YouTube, WhatsApp, Instagram, and WeChat. The top five platforms consist of three social network sites (Facebook, WhatsApp, and WeChat) and two media sharing networks (YouTube, and Instagram). Globally, internet users use an average of seven to eight different social media platforms each month (We Are Social, 2022b).

The literature highlights that platform preferences can be influenced by various factors. These include individual characteristics about the user, such as demographic attributes like age, and psychographic attributes like personality, and can also be influenced by the topic of the message or content. When examining the age demographic, Arora et al. (2018) found that Millennials use social media for a number of reasons, the main three reasons being to connect with new people, to receive information about products, and to keep up with news. Considering these three main uses, Arora et al.'s (2018) study on Millennials' social media platform preferences revealed Facebook as the most preferred social media platform, followed closely by YouTube and Instagram; Twitter and LinkedIn were the least preferred platforms.

Similarly, Shane-Simpson et al. (2018) also conducted a survey to understand the preferences of social media platforms. Their study of 663 college students found that characteristics including age, gender, functionality of the platform, and concerns regarding privacy, all impact social media platform preferences (Shane-Simpson et al., 2018). Focusing specifically on the demographic attribute of age, findings of the study suggest that younger people prefer newer platforms like Twitter and Instagram, whereas older people prefer Facebook (Shane-Simpson et al., 2018). This is further supported by industry reports which suggest there may be differences with regard to the social media platforms frequented by different age categories. For example, a United Kingdom report by market research company, eMarketer, suggested that older people are more likely to use Facebook, whilst younger age categories are using newer platforms (Fisher, 2020). Additionally, a report by YPulse also revealed some differences in the use and preferences for social media platforms by diverse age categories. Instagram was found to be popular amongst 13 to 18-year-olds, whereas Facebook was the most popular platform amongst the 26–37 age group (YPulse, 2020).

Another key finding of Shane-Simpson et al.'s (2018) study highlighted that preferences for social media platforms are influenced considerably by the types of communication and interaction features available on the platforms (Shane-Simpson et al., 2018). However, as social media platforms develop and integrate new features, a platform's initial specialisation is extended by the addition of other message format options, with many platforms offering similar features. For example, when Instagram was first release it was purely an image-sharing platform (Blystone, 2020); however, it can now be considered more broadly as a media-sharing platform due to the added features and message format options, including video. The varied options available on different platforms, and within platforms, highlights the need for considered decision-making by those who wish to use social media to convey messages.

A further consideration when deciding where and how to share a message is that users' platform preferences can change depending on the topic or content being conveyed in the message. In Lee et al.'s (2017) study, the researchers sought to understand the platform preferences of users who utilise more than one platform and discovered that their preferred platform depended on the topic of interest or topic being consumed. For example, the preference for food-related topics was Instagram; however, for daily matters, Twitter was the preferred platform. Another example of platform preferences that are influenced by the topic can be found in Polger and Sich's (2019) study which discusses the preferences of social media platforms in relation to students receiving information about their academic library. Their study revealed that in this context, participants (students) preferred social media platforms Facebook and YouTube to receive information. Specific to health and wellbeing topics, through a survey of 210 social media and search engine users, De Choudhury et al. (2014) determined the preferred platform in regard to online health activities. Although the study participants prefer search engines when searching for information on serious health conditions, social media platforms such as Twitter are used to share information on more benign health issues and symptoms.

The literature highlights that the varying platform preferences can depend on factors such as the topic focus of the message and an individual's age. However, it is unknown how this translates to the context of health and wellbeing messages which can have broad age appeal. Findings from the current study may provide useful insights for micro-influencers

when creating messages to disseminate to age-diverse audiences. In particular, the current study could inform when and how they could alter their message type or message format, depending on the platform preferences of audiences and if they differ among certain age categories.

2.6.2. Preferences of Social Media Message Format

The existing literature on audiences' preferences regarding social media message format is quite limited and typically focuses on specific aspects of messages and within particular contexts. Furthermore, the research is generally not specific to messages shared on social media. However, extant literature has identified preferences for message strategies from a more macro-level perspective. For example, Nobles et al.'s (2020) study involved participants from different age groups and who live in under-served areas of Bristol in the United Kingdom. Seventeen adults under 18 years old, 11 adults between the ages of 19 and 65 years, 5 adults aged 65 plus years, and 5 Somali women between the ages of 19 and 65 years were invited to participate in a workshop which sought to understand the preferences of under-served community groups regarding public communication about the benefits of physical activity and the associated guidelines. Results revealed that visual communication was a preferred format when communicating a message, and social media platforms were identified as one potential avenue to enable better communication.

Additionally, an industry study on digital trends found that age can have a considerable impact on format preferences (An, 2017). Millennials were seen to have a strong preference for video content in comparison to Generation X and Baby Boomers who prefer text-based content (An, 2017). However, it is important to note that since this report was published in 2017, the number of older adults using social media has increased substantially (Vogels, 2019), which may impact conclusions which can be drawn on the preferred message format of older age categories.

The limited research into message format preferences, particularly in relation to social media platforms and in relation to age, suggests an imperative for this current study to examine message format preferences by social media platform and age. The results will have the potential to inform social media and influencer marketing and communication

strategies to enable more tailored communication with age-diverse audiences by creating messages in the format they most prefer.

2.6.3. Preferences of Social Media Message Type

Similar to preferences for message format, there are limited studies that investigate audience preferences for message type on social media. Specific preferences for elements of messages such as language, tone, spelling, grammar, punctuation, the use of emoticons, and the use of textese (abbreviations) are the areas that have been studied by scholars thus far (Kuerbis et al., 2017; Muench et al., 2014; Nobles et al., 2020).

A number of studies found that audiences' preferences regarding language used in health-related messages can affect the impact of the message. For example, when investigating whether there are global messaging preferences for different types of language content in the context of mobile messaging interventions for mental health, Muench et al. (2014) discovered that audiences are sensitive to the language used in messages which can have implications for the receptivity of the message by audiences. Studies have also found that communications that do not use textese, use accurate grammar, spelling and punctuation, are free of complex jargon, and instead are constructed using simple terminology, are typically preferred by audiences (Kuerbis et al., 2017; Muench et al., 2014; Nobles et al., 2020).

Studies have also shown that audiences have preferences for message tone. Tone is an important aspect of message creation as it can impact how well the message is received by audiences and the level of audience engagement (Muench et al., 2014). In Muench et al.'s (2014) study, which investigated messaging preferences in the context of message interventions for mental health and health-related conditions, the use of humour to communicate a message was not favoured by participants. Kuerbis et al.'s (2017) findings supported Muench et al.'s (2014) in that the use of humour should be avoided and is not preferred by both young and older adults. Nobles et al.'s (2020) study revealed that regarding health-related topics, instructive or clinical tones were also not well received by the public.

Furthermore, through an online survey of 277 adults, Kuerbis et al. (2017) found that message preferences do differ in some categories depending on age. For instance, older adults preferred positive emoticons as opposed to negative emoticons; however, for adults over 50 years, the results indicated that it would be wise to avoid using emoticons altogether. Adults over the age of 50 also preferred the use of 'you' instead of 'we' (Kuerbis et al., 2017), whereas younger people prefer the opposite (Muench et al., 2014).

The studies discussed herein have identified very specific aspects of message types that could be considered when creating messages (Kuerbis et al., 2017; Muench et al., 2014; Nobles et al., 2020) and some have uncovered areas of divergence between age groups. However, to the author's knowledge, no studies have yet investigated audiences' preferred message type (rational, informational, transactional, and transformational) or message formats (video, photo, text) and social media platforms in the context of micro-influencers who focus on health and wellbeing and whether audiences' preferences vary across diverse age categories.

Table 2 provides a summary of the literature and the identified gaps which this study addresses.

Table 2: Literature review

Researcher/s	**Focus**	**Findings**	**Knowledge Gaps**
Byrne et al. (2017)	Digital influencers	Influencers play a fundamental role in public health promotion, especially in motivating audiences to adopt a healthier diet.	These studies explored influencer marketing but did not explicitly examine the use of micro-influencers in the health and wellbeing context.
Kostygina et al. (2020)		Use of digital influencers can result in greater reach and improve interest and engagement.	
Nobles et al. (2020)		The use of influential and trusted individuals or organisations in the community is a valuable method to deliver messaging around benefits of physical activity.	
Alampi (2019)	Level of interaction, engagement and	Compared to celebrity endorsers, micro-influencers' are perceived as more authentic and accessible and their messages shared on	There are limited investigations on the use of micro-influencers who
Campbell and Farrell (2020)			

Trziszka (2021)	accessibility of micro-influencers	social media have resulted in better engagement metrics.	share messages about health and wellbeing-related topics.
Marques et al. (2020)			
Guner & Acarturk (2020)	Social media users	Investigated the use and acceptance of ICT by senior citizens and makes the comparison to a younger age category. This study applied the technology acceptance model. Although seniors expressed constraints to using social media, they were interested in learning and using the technology.	Each of these studies focus on various aspects of technology and social media practices. The one study that compares different age categories does not focus on social media or micro-influencer message strategies.
Kim et al. (2019)		Examined seniors' motivations for using social media network sites in the context of tourism-related activities and found a need for simple, beneficial, and compatible sites.	
Dumbrell and Steele (2014)		Adults aged 55 plus use social media to find and access information.	
Arora et al. (2018)	Social media message strategy preferences	The millennial age category use social media to connect with new people, receive information about products, and keep up with news. Facebook was the most preferred social media platform.	Two of these studies have examined social media message strategy preferences of specific age categories without any comparison across age-diverse audiences. The study that focused on comparison across ages did not focus on social media and micro-influencer health and wellbeing messages. All three of these studies focused on one element of a message strategy.
Shane-Simpson et al. (2018)		Focused on 18–25 year-olds' social media platform preferences. The younger participants in this sample preferred Twitter and Instagram, older participants preferred Facebook.	
Kuerbis et al. (2017)		Investigated the use of 18–70 year olds and focused on mobile devices and specific elements including language used and emoticons.	

Moran et al. (2019)	Media richness theory	The richness of the media influences engagement behaviour. Specifically, higher forms of media richness (such as image and video) result in higher engagement.	Micro-influencers who share health and wellbeing messages has not yet been examined in relation to the media richness theory.
Shahbaznezhad et al. (2021)		Focus on the airline industry and how different media rich message formats and platforms moderate the relationship between the presence of message types and engagement behaviour. Results showed that message type effectiveness does vary based on message format and social media platform.	
Leung et al. (2017)		Focus on the hotel industry and developed a typology of message formats and message types for social media marketing.	

Whilst there are industry reports that provide some insight into the practices of audiences of diverse ages generally and in relation to micro-influencers, there is limited academic research. Filling this gap is particularly important, given that digital inclusion has been identified as a priority for the Department of Health and Wellbeing (Office for Ageing Well, 2019) and communicating effectively requires aligning media with the information needs of the audience (Daft & Lengel, 1983). This leads to the first research question which asks:

> ***RQ1***: How do social media practices, generally and in relation to micro-influencers, vary among age-diverse audiences?

Limited research has investigated what social media message strategies audiences of micro-influencers prefer in the context of health and wellbeing. This research will address this gap to substantially assist in ensuring that important health and wellbeing messages are better constructed and tailored for target audiences for all age categories to not only consume but to engage with and understand.

This leads to the second research question which asks:

> ***RQ2:*** What social media message strategies do audiences of health and wellbeing micro-influencers prefer? Specifically:

a) What social media platforms do audiences of health and wellbeing micro-influencers prefer?
b) What social media message formats do audiences of health and wellbeing micro-influencers prefer?
c) What social media message types do audiences of health and wellbeing micro-influencers prefer?

Additionally, given that the literature (as discussed in sections 2.1.3. and 2.3.1.) highlights the increasing use of social media by age-diverse audiences to connect with and receive messages about health and wellbeing, and that both age and social media platforms may impact audiences' preferences, research question 3 asks,

> ***RQ3:*** How do the audiences' preferences for message strategies vary based on social media platforms and among age-diverse audiences?

To interrogate RQ3 there is a need to examine the relationships between social media platforms, audiences' age and social media message format and message type preferences. As such, the following hypotheses are proposed:

> *H1*$_a$: Audience age moderates the effect of message format on audiences' message strategy preferences.
>
> *H1*$_b$: Social media platform preference moderates the effect of message format on audiences' message strategy preferences.
>
> *H2*$_a$: Audience age moderates the effect of message type on audiences' message strategy preferences.
>
> *H2*$_b$: Social media platform preference moderates the effect of message type on audiences' message strategy preferences.

2.7. Chapter Summary

Although the literature shows that studies have been conducted to understand platform preferences (Arora et al., 2018; Shane-Simpson et al., 2018), very limited research has been conducted to determine the social media platform, social media message format, and social media message type preferences of age-diverse audiences when consuming messages or content being shared by micro-influencers who have a health and wellbeing focus.

Additionally, whilst there are industry reports which provide insight into the social media practices of age-diverse audiences (Auxier & Anderson, 2021; Vogels, 2019), limited scholarly research has explored this area. As discussed in section 2.2.2., micro-influencers are considered valuable in communicating messages and, along with the growing number of social media users across age categories and increasing communication of health and wellbeing messages on social media, it is important to understand what social media platforms, message formats, and message types are preferred by audiences of different ages when consuming these topics. By building an understanding of the social media practices of age-diverse audiences and their preferred micro-influencer message strategies, micro-influencers who focus on health and wellbeing, and those that utilise micro-influencers for health and wellbeing communication, can better understand how best to tailor and align their messages to the information needs of audiences and receive positive and improved outcomes, such as positive performance metrics, or increased connection and engagement with audiences.

Moving forward, the following conceptual model (Figure 1) highlights the key areas identified in the literature review which will be further investigated in this study.

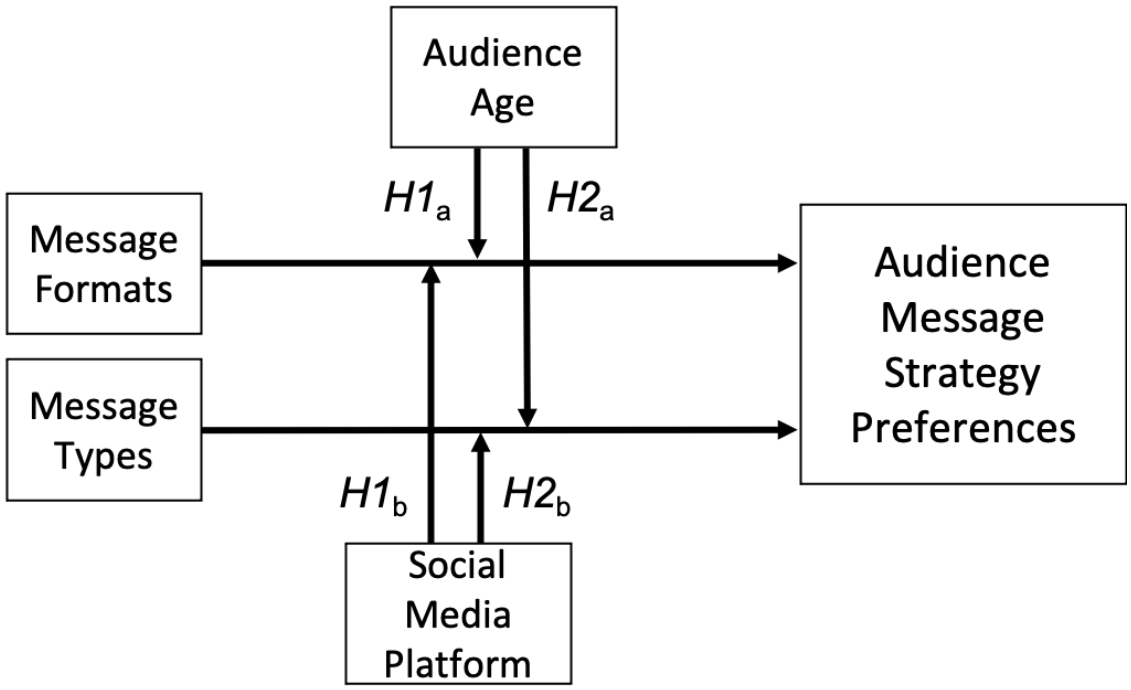


Figure 1: Conceptual model: audience age and social media platform (using social media platform preference) moderates audiences' message strategy preferences

Chapter Three: Methodology

The previous chapter discussed the imperative for this research and the need to better understand the social media practices and message strategy preferences of age-diverse audiences to inform how health and wellbeing messages can be tailored by micro-influencers to align with the information needs of audiences of diverse ages.

The purpose of this chapter is to outline the methodology and methods employed to address the three research questions, namely:

1) How do social media practices, generally and in relation to micro-influencers, vary among age-diverse audiences?
2) What social media message strategies do audiences of health and wellbeing micro-influencers prefer?
3) How do the audiences' preferences for message strategies vary based on social media platforms and among age-diverse audiences?

This chapter outlines the research design employed in this study, theory and approach underpinning discrete choice experiments to enable the examination of audiences' preferred micro-influencer message strategies, data collection method, recruitment strategies employed, ethical considerations, sample details, and data analysis techniques.

3.1. Research Design

This study employed a cross-sectional research design to investigate the social media practices and micro-influencer health and wellbeing message strategies preferred by age-diverse audiences. As outlined in the literature review, and for the purposes of this study, message strategies include social media platform (for example, Facebook and Instagram), message format (picture, text, and video), and message type (rational, transactional, interactional, and transformational).

A cross-sectional design was employed because it enabled the researcher to examine the social media practices of an age-diverse audience and, through testing hypotheses, to examine and explain the associations/relationships between variables – for example, audiences' social media platform preferences and message strategy (message format and

type) preferences by age categories. The aim was also to investigate whether 'age' and 'social media platform preference' moderate message format and message type preference. The design allowed for the study sample to be categorised based on existing differences within the population, which, for the purpose of this study, was age.

The research design is underpinned by a positivist paradigm, where objectivity and explanation of measurable constructs are underpinning assumptions (Park et al., 2020). A positivist paradigm relies on objectivity, deductive logic and formulation and testing of hypotheses (Antwi & Hamza, 2015). One of the primary goals of positivist research is to generate explanatory associations that lead to prediction (Park et al., 2020). Positivist approaches can inform us about how individuals perceive the world (Baškarada & Koronios, 2018), by utilising the processes of gathering numerical data, observing regularities, and extracting laws (Kankam, 2019). As such, a positivist paradigm was deemed best suited to underpin the current study as it aligned with the research questions and enabled quantifiable observations of the social media message strategies preferred by age-diverse audiences.

The cross-sectional design positioned within a positivist paradigm is observational in nature and focuses on investigating and drawing inferences from existing differences between people, subjects, or phenomena at a specific point in time (Bethlehem, 1999). Cross-sectional studies are considered an appropriate design for identifying associations and relationships between variables (Mann, 2003), and can play an important role in theory development (Finan et al., 2020). This type of design is especially useful when little is known about a new domain, to investigate a new variable in an existing domain, or to examine the role of moderating variables (Spector, 2019). Further advantages of a cross-sectional survey include the efficiency of the data collection process and the potential sample reach (Spector, 2019).

The next section will outline the method employed in the current study and the underpinning theory and approach in the development of the cross-sectional online survey instrument.

3.2. Method: Cross-sectional Online Survey Incorporating Discrete Choice Experiment

To enable inferences to be drawn about age-diverse audiences of micro-influencers at a particular point in time (Hall, 2008) when consuming health and wellbeing messages, a cross-sectional online survey, which incorporated a discrete choice task, was designed and disseminated to social media users. Social media users were invited to participate to provide information about their social media practices, and preferences regarding social media message strategies, inclusive of the social media platform, message format, and message type employed by micro-influencers in the health and wellbeing area.

3.2.1. Stated Preference Approach and Discrete Choice Experiment

A discrete choice experiment was incorporated as the main component of the online survey to enable examination of the preferences of an age-diverse audience in relation to micro-influencers' social media message strategies. A discrete choice experiment was considered the most appropriate approach as it is a choice elicitation method which uses the *stated preference* approach in a way that closely mirrors real-life choices (Merino-Castello, 2003; Turner and Coote, 2017) to understand participants' preferences regarding a certain phenomenon (Mangham et al., 2009). In this current study, the discrete choice experiment involved participants choosing between 12 combinations of message format and message type to comprise a message strategy; this is further outlined in Table 4. This section will further explain the rationale for selecting the *Stated Preference* approach, along with the specifics of the discrete choice component of the survey.

There are a number of ways to elicit preferences from a group of people. Two key methods are *revealed preference* and *stated preference* (Louviere, 2001). *Revealed preference* data is where people are observed whilst making actual decisions, and preferences are then inferred from what was chosen and what was rejected in real-life scenarios (Louviere, 2001). *Stated preference* methods are based on surveys and experiments where respondents are presented with real-life scenarios or hypothetical markets and are asked for choice responses (Louviere et al., 2000). Research or applied problems that surround changes in technology can be addressed with great insight from stated preference data (Louviere et al., 2000). Stated preference data can, for instance, help organisations and brands develop and

determine important elements within a business plan and marketing strategy that can impact the success of the brand and the product or service being offered. These elements include determining the appropriate target market, customer segments, and understanding the demand for a product or service (Louviere et al., 2000).

A beneficial aspect of *stated preference* methods over *revealed preference* methods is that the choice alternatives/scenarios can be existing, proposed or hypothetical alternatives, and unbranded or unlabelled (Louviere et al., 2000). The characteristics of *stated preference* methods provide researchers or those in industry more scope to investigate consumers' choices in relation to something that may not be as feasible to investigate in a revealed preference setting. In this study, for example, it was determined that understanding participants' preferences in relation to message strategies (comprised of a combination of message format and message type) in a real-world setting, that is, on a social media platform, was not feasible because it would not have been possible to predetermine the message strategies that participants would view when scrolling through their social media accounts due to social media algorithms which determine the content on a user's feed.

Whilst a limitation of stated preference methods is that in some instances it may not effectively represent changes in the market and personal constraints unique to an individual (Louviere et al., 2000), *stated preference* methods best suited the current study design and topic being investigated. The variables being examined, specifically message formats and message types, are foundational aspects of content and message creation that people, including micro-influencers, consider when creating social media content.

There are three methods that draw on the stated preference approach: contingent valuation, conjoint analysis, and (discrete) choice experiment (Merino-Castello, 2003) (see Figure 2 for a complete outline of stated preference methods). Contingent valuation was eliminated as a data collection method as this is an economic technique and typically measures consumers' willingness-to-pay or willingness-to-accept a potential change in the level of provision of a good or service (Merino-Castello, 2003). Conjoint analysis and choice experiment are both multi-attribute valuation techniques whereby more than one attribute of a concept, which in this study is the message strategy, is investigated and analysed. Although conjoint analysis and choice experiment have this commonality, they otherwise

differ greatly. Where conjoint analysis is a preference-based approach that asks participants to rank or rate all alternative options presented, discrete choice experiment is a choice-based approach that asks participants to choose among alternative options that are presented to them (Mangham et al., 2009; Merino-Castello, 2003; Turner and Coote, 2017); that is, only one selection is made.

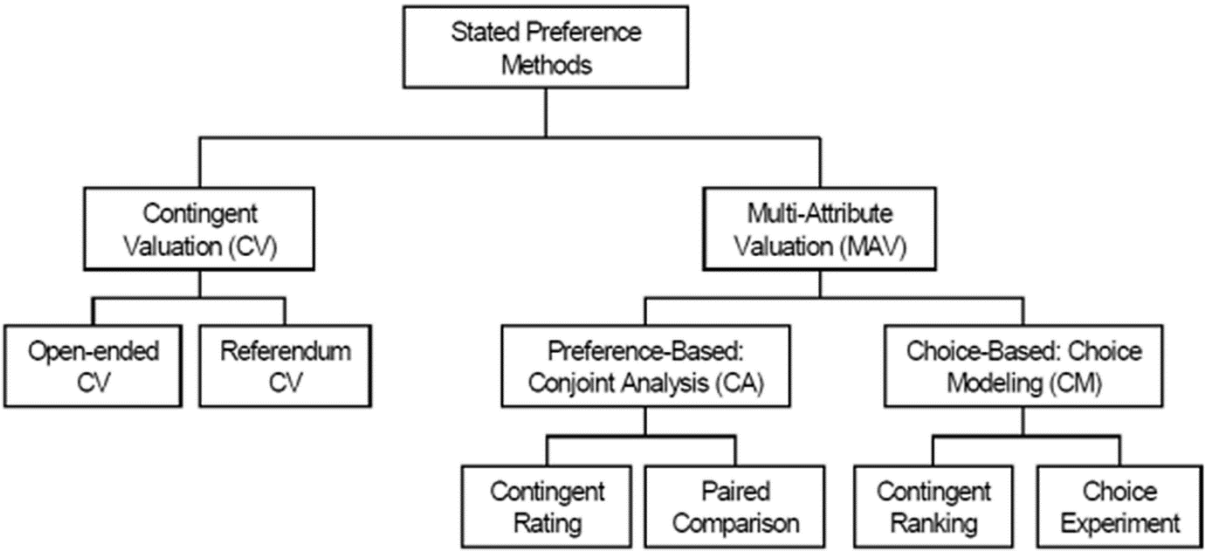


Figure 2: Stated preference methods (Merino-Castello, 2003)

Within a discrete choice experiment, choice sets are generated to simulate real-world decisions and study participants 'state' what their choices would be, as opposed to researchers observing participants' choices (revealed preference). Choice-based methods, especially discrete choice experiments, are favoured amongst scholars in comparison to preference-based methods, and even other choice-based methods, as they are considered more realistic and more closely resemble, or simulate, actual choices (Merino-Castello, 2003; Turner and Coote, 2017). This is because real markets often involve several competing choice options, including the option of choosing more than one option, or no option at all. For these reasons, discrete choice experiment was determined to be the most appropriate data collection method to address the research questions. An important point to note, however, is that although discrete choice experiments most closely represent real-life choices, responses measure the most preferred option relative to the remaining options and does not allow for observations about a participant's preferences among the options that are not chosen (Louviere et al., 2000). With regard to this study, this means that whilst a participant has selected one option as their message strategy preference for each choice

set, the study does not provide insight into their preferences among the message strategies they did not choose.

3.2.2. Discrete Choice Experiments and Random Utility Theory

Discrete choice experiments are underpinned by an established and well-tested behavioural theory, Random Utility Theory (RUT) (Louivere, 2001). RUT evolved from Thurstone's (1927) Law of Comparative Judgement (Louivere, 2001) which is a psychological perspective on binary choice theory (Brown and Peterson, 2009). The Law of Comparative Judgement posits a discriminal process; that is, when an individual draws comparisons between options presented, value is determined by the attributes that make up the options, and the traits and attitudes of the individual (Thurstone, 1927). McFadden (1973, 1986) expanded on this theory which we now know as RUT.

RUT suggests that utility (U_{in}) exists for every choice alternative and is a latent construct because it cannot be observed by researchers. Latent utilities comprise two components: a systematic component (V_{in}) which is explainable, and a random component (ε_{in}) which is unexplainable. The systematic components can be explained by researchers as they include 1) attributes which represent differences in choice alternatives, and 2) variables that may explain differences in individuals' choices, such as age. The random components consist of all unidentified factors that have the ability to impact individuals' choices (Louviere et al., 2010). However, when valid preference elicitation procedures, such as a discrete choice experiment, are conducted, a part of the unobservable consumer utility (in this study that is preference) can be investigated and understood. It is important to note that there will always be a part of the random component of the utility that will remain unexplained (Louviere, 2001).

The following equation illustrates the RUT in which U_{in} is the latent utility of the choice alternative(i) for the individual (n), and V_{in} is the explainable systematic component of utility that individual (n) associates with choice alternative (i), and ε_{in} is the unexplainable random component of the utility that the individual (n) associates with choice alternative.

$$U_{in} = V_{in} + \varepsilon_{in}$$

A number of statistical models, for example, discrete choice models, can be used to determine preference in response to choice options and their attributes, such as message type and message format, and possible covariates, such as age, thereby differentiating decision-makers from one another (Louivere et al., 2010). The following equation illustrates the probability of an individual n choosing option i from all j options in choice set C_n. Max signifies the maximum operator.

$$P(i|C_n) = P[(V_{in} + \varepsilon_{in}) > Max(V_{jn} + \varepsilon_{jn})]$$

This equation states that the probability of individual n choosing option i from the choice set C_n is equal to the probability that the explainable systematic component V_{in} and the unexplainable random component ε_{in} of option i for the individual n are greater than the explainable systematic component V_{jn} and the unexplainable random component ε_{jn} of all other options in the same choice set.

The next section will detail the specific steps employed to conduct the discrete choice experiment.

3.2.3. Discrete Choice Experiment Steps

To reiterate, a discrete choice experiment is a quantitative method for establishing individual preferences for a particular phenomenon (Mangham et al., 2009) and it was a key component of the cross-sectional survey. Section 7 of the survey invited respondents to nominate their preferences for hypothetical scenarios (Mangham et al., 2009) which enabled investigation into what characteristics of the phenomenon are preferred, that being message strategy preferences preferred by the individual when consuming health and wellbeing messages shared by micro-influencers (Oluboyede et al., 2019). The participants were presented with sets of realistic but hypothetical scenarios consisting of attributes and levels in which they had to determine their preference over the sets (Mangham et al., 2009). An example of a hypothetical scenario in a choice set was the message format 'Text' (message format being the attribute, and text being a level of that attribute), and the message type 'Promotional' (message type being the attribute, and promotional being a level of that attribute). As mentioned in section 3.2.1., as opposed to other preference techniques such as ranking or rating preferences, the options chosen by respondents enable

researchers to determine the attributes a participant values and prefers out of the choice sets presented to them. Discrete choice experiments determine this value in a way that more closely represents decision-making in real-world environments, where individuals need to make trade-offs between the options presented to them (Mangham et al., 2009; Turner & Coote, 2017).

Conducting a discrete choice experiment involves ten steps (Turner & Coote, 2017) which can be further organised into three phases (see Figure 3).

Phase 1: Conceptualisation	1. Characterise the choice design
	2. Identify the attributes and levels
Phase 2: Experimental Design	3. Select the choice experiment design
	4. Create the survey
	5. Plan data collection and recruitment strategies
	6. Administer pilot test
	7. Disseminate the survey
Phase 3: Analysis	8. Undertake coding
	9. Select a model
	10. Interpret the findings

Figure 3: Steps and phases in a discrete choice experiment (adapted from Turner & Coote, 2017)

The following section will detail Steps 1–4 of conducting the discrete choice experiment, which covers Phase 1 and part of Phase 2, up to and including creating the survey.

In Step 1, the research problem provides context and the rationale why a discrete choice experiment was considered the most appropriate method to address the research questions in the current study is identified. Steps 2 to 4 outline how the discrete choice element was incorporated in the online survey. The remaining steps either have been, or will be, discussed in the following sections of this chapter (section 3.3. for creation of the survey, section 3.3.1. for survey pilot testing, section 3.4.2. for dissemination of the survey, and section 3.7. for data analysis).

Step 1: Identification of the problem

In Step 1, the problem and decision-making context (and options) of the problem need to be identified. The literature review (Chapter 2) provides the grounding for Step 1, whereby the context, problem and gap are identified through a critique of the literature. In the context of the current study, the problem and gap relate to opportunities to better leverage micro-influencer marketing for health and wellbeing messages (Appel et al., 2020; Campbell & Farrell, 2020; Hudders et al., 2020; Kim and Kim, 2022) for increasingly age-diverse social media users (Park et al., 2021; Pew Research Center, 2019; Vogels, 2019). To enable effective marketing and communication to occur, there is a need to understand the micro-influencer message strategies most preferred by age-diverse audiences so that important health and wellbeing messages can be tailored to preferences to try to maximise reach and uptake. The discrete choice experiment in this study provided participants the opportunity to choose which message strategies, that is, which combination of message format and message type, they most prefer when consuming health and wellbeing messages from micro-influencers. This aspect is the decision-making component of the problem that generated data to address the research questions.

Step 2: Identification of the attributes and levels

In Step 2, the attributes and levels need to be determined. The attributes and levels in the discrete choice were informed by the literature review (see Table 1 for a summary). Two attributes were included – 1) message format and 2) message type – as they were identified to be two main components of a message strategy (Leung et al., 2017; Shahbaznezhad et al., 2020) (Table 3).

With regard to message format, Enke and Borchers (2019) identified that written texts, pictures, and videos are the most important content/message formats for influencers when sharing their content and messages. Although other typologies of message format identified in the literature include Web Link (Leung et al., 2017), length of text and hashtags (Chae, 2020), Enke and Borchers (2019) identified three message formats specific to influencer messages. Therefore, this study also adopted written texts, pictures, and videos as the final three levels of message format attribute. Acknowledging that there are various approaches that can be considered when categorising message type, the review of literature revealed

four key message types which were subsequently included as levels in the discrete choice experiment: rational, transactional, interactional, and transformational. To provide more descriptive labelling for participants, more familiar and explanatory terms were used. As such, the language used to describe each of the four message types was altered to the following:

- Rational to **informative**
- Transactional to **promotional**
- Interactional to **interactive**
- Transformational to **emotional or relatable**

The operationalisation of the terms and the descriptive qualifiers (see Table 1: Categories of message type, in section 2.5.3.) informed the final terminology used in the survey (see Figure 5 for an example of how the attributes were presented in the online survey).

The language used to describe the three message formats remained unchanged.

Table 3: Attributes and levels for discrete choice experiment

ATTRIBUTES	LEVELS
Message Format	Written Text
	Pictures
	Video
Message Type	Rational (informative)
	Transactional (promotional)
	Interactional (interactive)
	Transformational (emotional or relatable)

Step 3: Selection of the choice design and the generation of choice sets

In Step 3, the choice design is selected, and the choice sets that will be presented to participants in the experiment are generated. The aim of this step was to select a choice design that enabled collection of the maximum amount of information from each participant (Huber & Zwerina, 1996). To ensure this occurred, the commonly used D-efficiency criterion (Mariel et al., 2021) was used. The D-efficiency 'tries to minimise the standard errors on the diagonal, while at the same time controlling for the degree of correlation between parameter estimates' (Mariel et al., 2021). The method ensured:

- levels of an attribute appeared with equal frequency in a choice set (Addelman, 1962); for example, each message format appeared 8 times, and each message type appeared 6 times
- levels of an attribute appeared with equal frequency within each version of the survey (Kuhfeld et al., 1994); in this study, each participant was shown all choice sets and therefore all levels of an attribute appeared with equal frequency in each survey
- levels of an attribute in each choice set were different (Bunch et al., 1996)

The discrete choice experiment design, inclusive of the 12 choice sets, was generated using analytics software, SAS Version 9.4M7 (SAS Institute, 2022). A computerised search algorithm within the program is used to generate the best and most efficient design (Johnson et al., 2013). A macro function is an algorithm used to program code in the SAS software and execute the commands. The macro function '*MktEx*' was used to generate the design for the discrete choice experiment used in the current study. This macro function creates D-efficient linear experimental designs (Kuhfled, 2010) with the ultimate aim of finding a design with the highest D-efficiency score and a low D-error score (Perez-Troncoso, 2020; Yap, 2018). These two scores are related, in that a higher D-efficiency score indicates a lower D-error score. The D-efficiency score and the D-error score, which is the inverse of D-efficiency (1/8.3859), are measurements that indicate how efficient a design is at extracting information from respondents (Yap, 2018). The higher the D-efficiency score, the more statistically efficient the experiment design is (Johnson et al., 2013; Vanniyasingam et al., 2018). As a D-value is case-specific and cannot be compared across studies, there is no specific threshold for an 'ideal' D-error value; however, a lower D-error value, less than 1,

which was achieved in the current study, is considered good and provides confidence that the data can be used for model estimation (Bliemer & Rose, 2014). The relative D-efficiency, which is used to measure the optimality of the model, is the D-efficiency divided by the optimal value (the number of choice sets) and multiplied by 100 (Kuhfeld, 2009). The relative D-efficiency value ranges from 0% to 100% and is 'a relative measure of hypothetical orthogonal designs' (Vanniuasingam et al., 2016). When balanced and orthogonal, a d-efficient design will have a value of 100% (Vanniuasingam et al., 2016). In instances where values fall between 0% and 100% all parameters are still estimable; however, they will have 'less precision than an optimal design' (Vanniuasingam et al., 2016).

After the MktEx macro was run to find the most efficient design, the OPTEX Procedure in SAS was then used to check and evaluate the design (Kuhfeld, 2010). As illustrated in Figure 4, out of 100 designs generated by SAS using the MktEx macro algorithm (see Appendix E for complete SAS output), Design 28 was the most statistically efficient, with a D-efficiency of 8.3859, a relative D-efficiency of 69.8827, and a D-error of 0.1192. This D-error value below 1 indicated that data was suitable for model estimation. This design included 12 choice sets, indicating a full factorial design.

The SAS System

Final Results

Design	28
Choice Sets	12
Alternatives	2
Parameters	5
Maximum Parameters	12
D-Efficiency	8.3859
Relative D-Eff	69.8827
D-Error	0.1192
1 / Choice Sets	0.0833

Figure 4: SAS output

A discrete choice experiment that uses all possible scenarios/existing combinations in the survey is known as a full factorial design (Hensher at al., 2005). As discussed above, the discrete choice experiment in this study consisted of two attributes: one attribute with three levels (Message Format), and one attribute with four levels (Message Type),

altogether generating 12 combinations or choice sets (see Table 4 for all 12 choice sets). All 12 combinations were presented to each participant in Section 7 of the survey and so this study was considered a full factorial design. The alternative design for studies with a large number of combinations is a fractional factorial design in which only a fraction of the total number of combinations is used in order to reduce the size of the experiment (Hensher et al., 2005; Mangham et al., 2009). However, given the number of ideal choice sets generated for the current study was 12, proceeding with a full factorial model was feasible and appropriate. A full factorial design also allows for estimation of both main effects and interaction effects (Mangham et al., 2009). A main effect can be described as 'the direct independent effect on the choice variable of the difference in attribute levels' (Mangham et al., 2009). For this study, a main effect is the direct effect of the difference in message format on the choice variable preference. An interaction effect refers to 'the effect on the choice variable obtained by varying two or more attribute levels together' (Mangham et al., 2009). Interaction effects in this study are each of the choice sets as they combine one message type and one message format with another message type and message format. A specific example is Choice Set 1, in which promotional text and interactive picture are presented to respondents simultaneously for an understanding of the trade-off among attributes and their levels.

Table 4: Discrete choice experiment choice sets

CHOICE SET	**MESSAGE STRATEGY**
CHOICE SET 1	Promotional Text Interactive Picture
CHOICE SET 2	Informative Picture Emotional or Relatable Text
CHOICE SET 3	Emotional or Relatable Video Promotional Text
CHOICE SET 4	Interactive Video Informative Text
CHOICE SET 5	Emotional or Relatable Picture

	Interactive Video
CHOICE SET 6	Promotional Picture Interactive Text
CHOICE SET 7	Informative Picture Emotional or Relatable
CHOICE SET 8	Informative Video Interactive Picture
CHOICE SET 9	Emotional or Relatable Picture Promotional Video
CHOICE SET 10	Interactive Text Emotional or Relatable Video
CHOICE SET 11	Informative Text Promotional Video
CHOICE SET 12	Promotional Picture Informative Video

Step 4: Creation of the survey

Step 4 involved creating the survey, which was hosted on Qualtrics XM (2022) (see Appendix B for the full survey). The next section will outline specific details regarding the online survey design.

3.3. Online Cross-sectional Survey Design

The survey was divided into seven sections: 1) participant demographics; 2) social media use and activity, 3) participant understanding and following of micro-influencers, 4) social media platform preferences, 5) message format preferences, 6) message type preferences, and 7)

a discrete choice experiment to determine message strategy preferences (inclusive of message format and message type).

Section one included demographic questions about age, gender identity, Australian citizenship and residency, postcode and if the participant identified as Aboriginal or Torres Strait Islander.

Section two asked participants about their social media use and activity. This included their social media account/s, if any, the device/s they use to access their social media accounts, if they considered themselves to be an active user of social media, the social media platform they are most active on, the time of the day they are most active on social media, how often they access their social media throughout the day, and what activities they most used social media for over the past week.

The first question in Section two, which asked if participants had a social media account, was a screening question. If participants selected 'no', they were redirected to the end of the survey, thanking them for their time and interest.

Section three of the survey asked questions related to micro-influencers. The first question asked participants if they followed any micro-influencers on social media. If they did not follow a micro-influencer, a follow-up question asked if they *would* follow a micro-influencer in the future. This second question was also a screening question – if the participant selected 'no' or 'unsure' they were redirected to the end of the survey with thanks. If participants answered 'yes' to the first question in the section, or if they did not follow a micro-influencer but selected 'yes' to the follow-up question (meaning they *would* follow a micro-influencer in the future), the branching logic enabled them to continue with the remaining survey. Those who indicated that they follow micro-influencers were asked three additional related questions, including why they follow micro-influencers, what platforms they follow micro-influencers on, and if they follow the same micro-influencer on more than one social media platform.

Section four asked participants about their social media platform preferences. They were asked, in a general sense, what their social media platform preferences were when viewing micro-influencer messages.

Section five asked participants about their *message format* preferences when using social media to view messages by micro-influencers and also their *message format* preferences with regard to their most preferred social media platform.

Section six followed question formats similar to section five, but instead asked participants about their *message type* preferences when using social media to view messages by micro-influencers and also their *message type* preferences in regard to their most preferred social media platform.

Section seven consisted of a discrete choice experiment where participants were presented with 12 different choice sets. Each choice set had two options to choose from, and each option consisted of one message format (picture, text, and video) and one message type (rational, transactional, interactional, and transformational). For each of the 12 choice sets, participants had to select which option, out of the two presented to them, they would most prefer to see when micro-influencers share health and wellbeing messages on social media. The final question in this section, and for the survey, asked participants if their preferences were likely to differ depending on the topic of the message.

Preferences about social media platforms were gathered through general survey questions. Preferences regarding *message format* and *message type* were gathered using the discrete choice experiment. Both closed and open-ended questions were used in this survey; in other words, some questions allowed participants to write in full sentence format, and some questions provided participants with a list of alternatives to choose from (Cavana et al., 2001). An example of an open-ended question was when asking whether their message strategy preferences were likely to differ depending on the topic of the message. A closed question example was when participants were asked to identify the type of device they most access their social media on from a list of options.

As this research is quantitative, most of the questions asked participants to select a response from the options provided. Survey branching was utilised to enable targeted survey items for followers of micro-influencers. Using the selected design, the discrete choice experiment, with each of the choice sets in a visually appealing format, were added to section seven of the survey. Figure 5 provides an example of how the discrete choice

experiment was presented to participants in the survey (see Appendix C for the complete discrete choice experiment presentation in the survey).

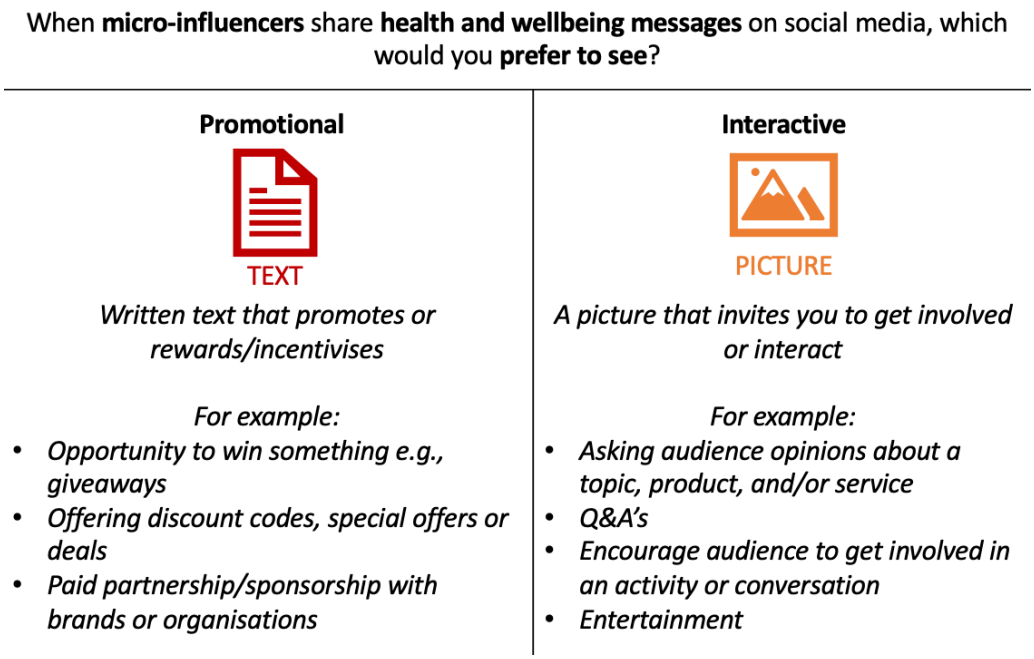


Figure 5: Presentation of a discrete choice experiment choice set in Qualtrics survey

3.3.1. Online Survey Testing and Piloting

Once the survey was finalised, and prior to public distribution, extensive survey testing was undertaken. The extensive testing approach enabled any concerns, questions, or suggestions regarding the survey to be addressed prior to public dissemination. The first stage of testing was completed by the researcher and supervisors and ensured that survey branch logic and discrete choice tasks worked as required and data was being collected in the database.

This was then followed by a small-scale pilot stage in which the survey was shared with a select number of invited participants from the researcher's network via direct messaging or email. Participants were asked to communicate with the researcher if there were any issues with the survey. The data collected at this stage were considered only tests and not included in the final dataset. Feedback from the second stage of testing revealed no major issues. After testing, the survey link was generated and included in all recruitment material.

The strategy used to distribute the survey included a staged release to continue to allow for any unforeseen issues with the survey and incoming data to be resolved before being more widely shared. Careful monitoring of incoming survey data throughout the recruitment process revealed no issues with survey data collection.

The second stage included those in the researcher's wider community and professional network, specifically, the survey was shared via the researcher's profile on various social media platforms. At the final and main stage, the survey was shared with micro-influencers, social media groups and local community groups.

3.4. Sampling and Participant Recruitment

This section outlines the sampling and recruitment strategies employed to recruit participants from diverse age categories.

3.4.1. Sampling

The study utilised non-probability sampling techniques. Convenience and purposive sampling approaches were employed through a maximum variation strategy. Although it is not possible to generalise results to the broader population, maximum variation, also known as heterogeneous sampling, helped to ensure that wide-ranging perspectives on the topic were collected (Etikan et al., 2016) across a wide range of age categories.

To draw meaningful and useful conclusions from the results with regard to the age variable, data was analysed by age categories (excluding those aged under 18) (see Table 5). The age categories used for analysis were in line with each generation as specified by Beresford Research (2022) with two changes: 1) the age categories used for this analysis do not separate the Baby Boomers into two separate categories, which is sometimes the case due to the large cohort in that generation, and 2) Baby Boomers and Post War generations were combined for analysis due to the small number of Post War respondents and to enable comparisons to be drawn in relation to the other age categories. A combination approach to generational age categories has also been used in other studies (for example, Martin & Pietsch, 2013; Ziemba & Eisenbardt, 2016).

Table 5: Age categories by generation

AGES	YEAR BORN	AGE CATEGORY
25 and under	1997–2012	Gen Z
26–41	1981–1996	Millennials
42–57	1965–1980	Gen X
58–76	1946–1964	Baby Boomers
77–94	1928–1945	Post War

3.4.2. Participant Recruitment Strategies

Given the aim to achieve maximum variation sampling, several strategies were implemented in a staged approach to recruit participants across a wide range of demographics, including age categories (see Appendix D for recruitment material). Four main strategies were employed:

1. Micro-influencers

   As part of the purposive sampling strategy, micro-influencers with wide-ranging health and wellbeing foci and who share health and wellbeing messages with their followers were identified and invited to participate and share the survey with their networks/followers. They were provided with the survey link and information about the survey. Micro-influencers were first identified based on the type of messages and content they post, specifically health and wellbeing-related content such as nutrition, and exercise and fitness. Next, to expand the reach of the survey, additional micro-influencers whose focus may not be solely on health and wellbeing but may include broader lifestyle topics, for example, gardening, were also identified. A key consideration for this part of the recruitment was to target micro-influencers who have followers of different ages or who typically attract a specific age category. This was established by first choosing micro-influencers of different ages and, second, choosing micro-influencers whose messages are typically directed towards a certain age category or across age categories. An example of the latter is a health and wellbeing micro-influencer who also shares parenting content. As followers of a micro-influencer often share similar interests or demographics with the micro-influencer (Tafesse & Wood, 2021), this means the audience would consist of parents who would therefore potentially sit within a certain age category. Communication in the first instance was directly to micro-influencers via Instagram

direct messaging. All micro-influencers identified and contacted were based in Australia.

2. Social media groups

   The survey link was shared in various online communities and groups on social media which either had a health and wellbeing focus and/or groups that targeted different age categories. These included Adelaide Health and Wellness Hub; Adelaide Spiritual and Wellbeing Events; Women's Wellness Daily; Athelstone, Rostrevor, Newton, Magill, Tranmere, Paradise & Campbelltown; Latinos en Adelaide; and Morialta Residents' Association. These groups were selected based on either the topic content (health and wellbeing), or the location of the group (South Australian-based groups).

3. Researcher's community and professional networks

   The survey was shared to people in the researcher's community and professional networks and on the researcher's social media platforms (Facebook, Instagram, and LinkedIn).

4. Local community groups (face-to-face/offline)

   Potential participants from local community groups were invited to face-to-face community meetings. As part of the purposive convenience sampling, this approach facilitated recruitment of an age-diverse audience, as members of the community groups tended to be in an older age demographic.

3.5. Ethical Considerations

3.5.1. Ethics Approval

This research adhered to the protocols and procedures outlined in the *National Statement on Ethical Conduct in Human Research* (NSECHR) *(2007 (Updated 2018))* which include the four values and principles that apply to all human research, namely: respect, research merit and integrity, justice, and beneficence. The main themes in research ethics include risk, benefit, and consent. The required University of South Australia (UniSA) ethics application, including the negligible risk ethics application, was completed and approved by the UniSA

Business Ethics Committee (UniSA Ethics Number: 056-2021) (see Appendix A). Ethical protocols were adhered to, including respecting the privacy and information of each participant and obtaining informed participant consent. Additionally, although security of data online cannot be guaranteed, every endeavour was made to secure data. Data was stored in locked/password protected folders on UniSA's server.

3.5.2. Participant Consent

Participants were provided with a consent form and information sheet within the online survey at the very start. They outlined the nature of the study; what would be required if the participant was interested in joining the study, including details about the voluntary nature of participation and the participant's right to withdraw at any time without any penalty; and the contact details of the researcher, supervisor and the ethics committee representative. If participants did not consent to participate, they were directed to the end of the survey and thanked for their time. Additionally, if a participant indicated that they were not aged 18 years or over, they were thanked for their interest but redirected to the end of the survey as they did not meet the selection criteria. Not only did those under 18 fall outside the proposed sample age parameters but they were also considered minors who would have required parental/carer consent to participate. Participants were also notified in the information sheet about the incentive for completing the survey; that is, for every participant who completed the survey, $1 would be donated to the National Breast Cancer Foundation. If participants wanted a summary of the results upon completion of the research project, they were invited to provide an email address at the end of the survey which was stored separately from survey responses to maintain survey response anonymity.

3.6. Sample Survey Screening and Sample Demographics

3.6.1. Sample Screening

The use of survey branching enabled only eligible participants to complete the survey. Participants:

- had to be aged 18 or older and
- have at least one social media account and
- had to follow a micro-influencer or intend to do so in the future.

3.6.2. Sample

After data cleaning was conducted (discussed in section 3.7.1.), the final number of responses included in this study was 375 (see Table 6 for a summary of total sample demographics). When examining gender identity, 25.6% (*n* = 96) of participants were male, and 73.6% (*n* = 276) were female. A further two participants identified as non-binary (0.5%), and one participant (0.3%) chose not to disclose their gender. Additional demographic data showed that 316 participants (84.3%) were Australian citizens, 2 out of the 375 participants (0.5%) identified as Aboriginal or Torres Strait Islander, and 360 participants (96%) currently reside in Australia.

Table 6: Summary of total sample demographics

Characteristic		**Frequency (*N*)**	**Percentage (%)***
Age			
18–25	Gen Z	114	30.4
26–41	Millennials	128	34.1
42–57	Gen X	91	24.3
58–76	Baby Boomers	40	10.7
77–94	Post War	2	0.5
Total		375	100
Gender			
Female		276	73.6
Male		96	25.6
Non-binary		2	0.5
Did not disclose		1	0.3
Total		375	100
Australian Citizen			
Yes		316	84.3
No		59	15.7
Total		375	100
Identify as Aboriginal or Torres Strait Islander			
Yes		2	0.5
No		373	99.5
Total		375	100
Reside in Australia			
Yes		360	96.0
No		15	4.0
Total		375	100

** Percentages have been rounded off to one decimal point*

Given that a primary variable of interest in this study is age (years), the following will provide information regarding the ages of participants, and will examine age in relation to other demographic variables, for example, gender.

The age of participants ranged from 18 to 78 years (*M* = 37.26, *Mdn* = 34, *SD* = 14.897). Age was non-normally distributed, with skewness of 0.695 (*SE* = 0.126) and kurtosis of -0.501 (*SE* = 0.251) (Figure 6). Whilst findings from this study cannot be generalised to the wider population, as a point of interest only, the median age of the study sample aligns closely with the median age of Australian citizens (*Mdn* = 38*)* (Australian Bureau of Statistics, 2022).

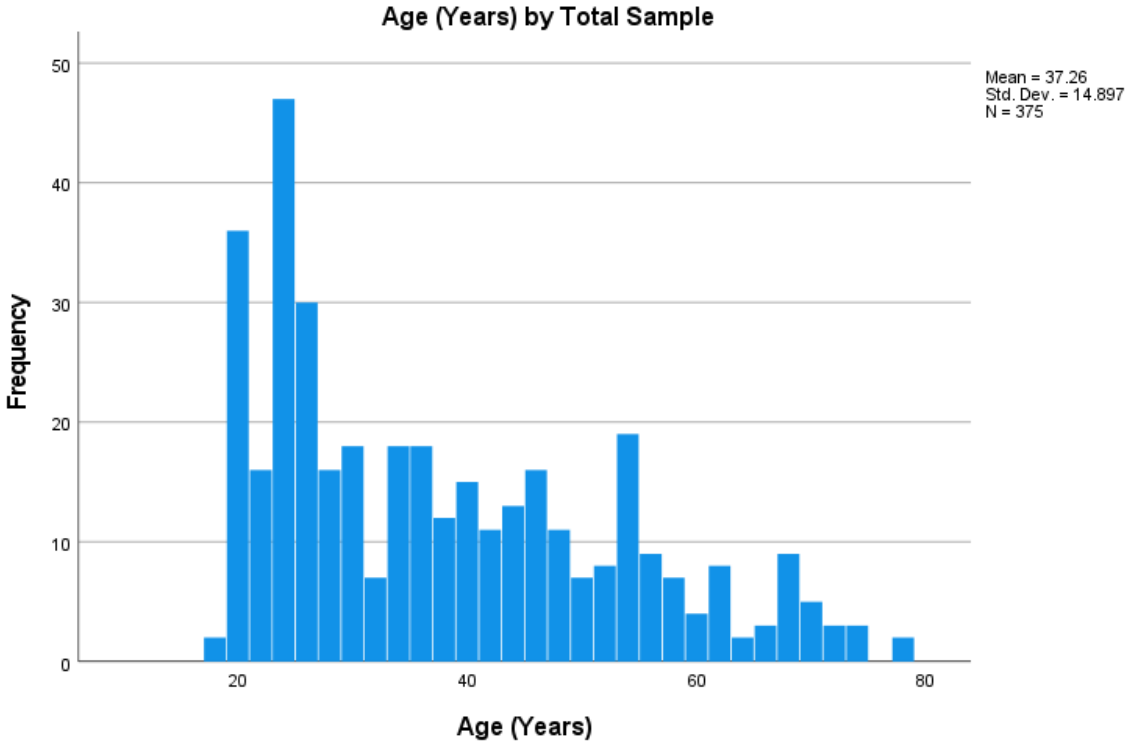


Figure 6: Age (years) by total sample

To facilitate meaningful analysis by age, the raw age variable was recoded to age categories, specifically drawing on generations, and included Generation Z (Gen Z), Millennials, Generation X (Gen X), Baby Boomers, and Post War participants (see Table 5). To facilitate analysis of cross-tabulations and chi-square tests, the Baby Boomers and Post War age categories were combined to help reduce the number of cell violations and to enable comparisons to be drawn in relation to the other age categories.

Table 7 below provides a summary of total sample age categories by gender. When examining age categories by gender, a cross-tabulation revealed the largest demographic group represented in the survey was Gen Z females (24%, *n* = 91).

Table 7: Cross-tabulation of age categories and gender

Gender	Age Categories				
	Gen Z	Millennials	Gen X	Baby Boomers	Post War
Male (*n* = 96)	21 (18.4)	45 (35.2)	19 (20.9)	9 (22.5)	2 (100.0)
Female (*n* = 276)	91 (79.8)	82 (64.1)	72 (79.1)	31 (77.5)	0 (0)
Non-binary (*n* = 2)	1 (0.9)	1 (0.8)	0 (0)	0 (0)	0 (0)
Prefer not to say (*n* = 1)	1 (0.9)	0 (0)	0 (0)	0 (0)	0 (0)
Total	114 (100)	128 (100)	91 (100)	40 (100)	2 (100)

Percentages within age category appear in parentheses below category frequencies.

These demographic variables, especially age, as it is the main variable of interest in this study, provided valuable contextual/background insights into the results generated, particularly in relation to understanding social media use and activity by various demographic groups and for understanding relationships between independent variables (for example, age) and dependent variables (for example, message strategy preference).

Of the 375 total survey participants, 221 completed the discrete choice experiment in Section 7 of the survey. Of the participants who completed the discrete choice experiment, the overwhelming majority (79.2%, *n* = 175) identified as female, 20.4% (*n* = 45) identified as male, and one participant did not disclose their gender. When examining Australian citizenship, 82.4% (*n* = 182) were Australian citizens and 17.6% (*n* = 39) were not. The majority of the participants resided in Australia at the time of the study (*n* = 210), and 5% (*n*

= 11) indicated they did not reside in Australia. A small minority of the sample (0.9%; *n* = 2) identified as Aboriginal or Torres Strait Islander. The age of participants who completed the discrete choice experiment ranged from 18 to 78 years (*M* = 33.85, *Mdn* = 30, *SD* = 12.971). Age was non-normally distributed, with skewness of 1.021 (*SE* = 0.164) and kurtosis of 0.419 (*SE* = 0.326). Table 8 provides a summary of participant demographics for those that completed the discrete choice experiment.

Table 8: Summary of discrete choice participants' demographics

Characteristic		**Frequency (*N*)**	**Percentage (%)***
Age			
18–25	Gen Z	80	36.2
26–41	Millennials	83	37.6
42–57	Gen X	45	20.4
58–76	Baby Boomers	12	5.4
77–94	Post War	1	0.5
Total		221	100
Gender			
Female		175	79.2
Male		45	20.4
Non-binary		0	0.0
Did not disclose		1	0.5
Total		221	100
Australian Citizen			
Yes		182	82.4
No		39	17.6
Total		221	100
Identify as Aboriginal or Torres Strait Islander			
Yes		2	0.9
No		219	99.1
Total		221	100
Reside in Australia			
Yes		210	95.0
No		11	5.0
Total		221	100

** Percentages have been rounded off to one decimal point*

3.7. Data Analysis

The online survey was closed after a three and a half month period (December 2021–mid-March 2022). Once the online survey was closed, the dataset was cleaned and prepared for data analysis.

3.7.1. Data Cleaning and Preparation

Prior to analysing the data, the online survey data that was collected was cleaned and prepared to enable accurate analysis. The data was cleaned in a number of phases to ensure accuracy.

Phase 1: Initial Clean

Once the survey data was downloaded from the Qualtrics online survey platform, all responses completed during the survey testing stage were removed (*n* = 87). Surveys in the testing stage were identified through the word 'test' being included in the first text box of the survey and were done prior to the survey being published (i.e., preview mode). This was then followed by removing responses from those who did not fit the inclusion criteria. Three screening questions were used to filter respondents for the data cleaning process. Any respondents who indicated that they were under 18 years old were removed from the data set in the first instance (*n* = 2), followed by the removal of participants who indicated they did not have a social media account (*n* = 12). The next consideration was whether the data by each participant was complete. The researcher decided to remove any responses from participants who did not complete the first two sections of the survey (demographics and social media use and activity) (*n* = 29), because without this data, the responses would not provide any comprehensive insights to sample characteristics or assist with answering the research questions. Following the data cleaning process, a total of 375 responses were used for analysis.

Phase 2: Recoding Variables

The next phase of the data cleaning and preparation process involved assigning and labelling variables, along with recoding several key variables. For example, age was recoded into age categories by generation to facilitate analysis (see Table 5 for the age categories used for analysis).

Phase 3: Preparation of Discrete Choice Data

The final phase of data cleaning was specific to the preparation of the data for the discrete choice analysis. Dummy coding of the data was conducted in order to enable statistical analysis (see Figure 7). This is discussed in detail in the discrete choice analysis section below (section 3.7.2.2.).

3.7.2. Data Analysis Techniques

Once data was cleaned, the researcher undertook descriptive analysis and discrete choice analysis, including binary logistic regression. Analysis was performed using IBM SPSS Statistics Version 28.0.1.1. (IBM SPSS Statistics, 2022) and Stata Version 17.0 (StataCorp, 2022).

3.7.2.1. Descriptive Analysis

Descriptive analysis, including frequencies, means, and standard deviations, were initially conducted to establish sample characteristics (Kemp et al., 2018) and to provide context to the study and the topic being investigated. Frequencies of each of the demographic questions were examined, including age, gender, Australian citizenship, Aboriginal or Torres Strait Islander, and Australian residency.

Frequencies were also gathered for questions in each of the subsequent sections, including social media use and activity, micro-influencers, preferred social media platform, preferred message format, and preferred message type.

To test for an association between two categorical variables of interest, for example, social media platforms participants were most active on and age categories, cross-tabulations and Pearson's chi-square test for independence were conducted. Additionally, to enable comparison at the cell level of each contingency table, adjusted standardised residuals were examined. This enabled the relative contribution of each cell to the chi-squared statistic to be assessed. A cell-by-cell comparison of expected and observed counts provides insight into the nature of the dependence (Agresti & Coull, 2002). Further, to address potential family-wise error and to account for Type 1 errors, which can occur when performing a series of follow-up comparisons in contingency table analysis, Bonferroni Correction was performed.

3.7.2.2. Discrete Choice Analysis

Discrete choice analysis, specifically binary logistic regression, identified the message format and message type preferences of age-diverse audiences within the sample of the current study. Analysis specific to discrete choice experiment comprises three stages. First, prior to data analysis, the data must be coded to determine parameter estimates (Turner & Coote, 2017) which then allows the data to be used for statistical analysis. Coding can be executed in two ways: dummy or effects coding. Dummy coding was used as it was identified as having reduced levels of data misinterpretation, especially when a categorical attribute has more than two levels (Hu et al., 2022). Dummy coding is the process in which the value of '1' indicates the presence of the level in the choice set option and the value of '0' indicates the level is not present. In this discrete choice experiment, the dependent variable is preference (the choice made by the respondent), and the independent variables are the levels that make up the attributes within each choice set (for example, video message format and interactive message type) (Turner & Coote, 2017). Once the independent variables (the levels comprising the choice sets) were dummy coded, the preference variable was dummy coded. If the participant selected the choice set option as their preference, the '1' value was also present (see Figure 6 for dummy coding and preparation of the data for analysis).

In the second stage of discrete choice analysis a model was selected which was then used to execute the third and final stage of the analysis phase: analysing and interpreting the findings from the discrete choice experiment (Turner & Coote, 2017). As each choice set consisted of two options for participants to choose from, as opposed to three or more options, the binary logit model was used to estimate the collective preferences of the respondents (Ryan et al., 2008; Turner & Coote, 2017). When conducting binary logistic regression, also known as binary logit, there are six main assumptions that have to be met (Laerd Statistics, n.d.). First, the dependent variable, which in this study is *preference of micro-influencer message strategy*, must be a dichotomous variable; that is, a variable with only two options. Second, there has to be two, or more independent variables. Third, observations in the sample are independent from each other and the dependent variable should have mutually exclusive categories. Fourth, the data must not show multicollinearity. Fifth, the relationship between the logit of the outcome and each continuous independent

variable is linear. The Box-Tidwell test is used to test this assumption; however, as none of the predictor variables used in this study were continuous this assumption was not applicable. Finally, the data should not have any significant outliers, high leverage points, or highly influential points.

The discrete choice analysis performed focused on four areas to understand whether preferences for:

1. message format vary based on age
2. message type vary based on age
3. message format vary based on social media platform (using the social media platform preference variable)
4. message type vary based on social media platform (using the social media platform preference variable)

A total of 221 participants completed the discrete choice experiment. This generated 2,652 choices made (that is, 221 participants by 12 choice sets) with 5,304 observations because each choice set had two alternatives to select as their preference.

Participant ID	Choice Set ID	Choice Set Option	Preference	Text	Picture	Video	Informative	Promotional	Interactive	Emotional or Relatable	Age	Age Group	Gender	AUS Citizen	Aboriginal/Torres Strait Islander	Reside in AUS	Have SM Account	No. SM Accounts	Active User	SM Most Active	Device Access SM
1	1	1	0	1	0	0	0	1	0	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	1	2	1	0	1	0	0	0	1	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	2	1	1	0	1	0	1	0	0	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	2	2	0	1	0	0	0	0	0	1	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	3	1	1	0	0	1	0	0	0	1	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	3	2	0	1	0	0	0	1	0	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	4	1	1	0	0	1	0	0	1	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	4	2	0	1	0	0	1	0	0	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	5	1	1	0	1	0	0	0	0	1	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	5	2	0	0	0	1	0	0	1	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	6	1	0	0	1	0	0	1	0	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	6	2	1	1	0	0	0	0	1	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	7	1	1	0	1	0	1	0	0	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	7	2	0	1	0	0	0	0	0	1	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	8	1	0	0	0	1	1	0	0	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	8	2	1	0	1	0	0	0	1	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	9	1	1	0	1	0	0	0	0	1	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	9	2	0	0	0	1	0	1	0	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	10	1	0	1	0	0	0	0	1	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	10	2	1	0	0	1	0	0	0	1	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	11	1	1	1	0	0	1	0	0	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	11	2	0	0	0	1	0	1	0	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	12	1	0	0	1	0	0	1	0	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
1	12	2	1	0	0	1	1	0	0	0	19	Gen Z	Female	Yes	No	Yes	Yes	8	Yes	Instagram	Smartphone
2	1	1	0	1	0	0	0	1	0	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	1	2	1	0	1	0	0	0	1	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	2	1	1	0	1	0	1	0	0	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	2	2	0	1	0	0	0	0	0	1	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	3	1	1	0	0	1	0	0	0	1	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	3	2	0	1	0	0	0	1	0	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	4	1	1	0	0	1	0	0	1	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	4	2	0	1	0	0	1	0	0	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	5	1	0	0	1	0	0	0	0	1	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	5	2	1	0	0	1	0	0	1	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	6	1	1	0	1	0	0	1	0	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	6	2	0	1	0	0	0	0	1	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	7	1	1	0	1	0	1	0	0	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	7	2	0	1	0	0	0	0	0	1	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	8	1	1	0	0	1	1	0	0	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	8	2	0	0	1	0	0	0	1	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	9	1	1	0	1	0	0	0	0	1	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	9	2	0	0	0	1	0	1	0	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	10	1	0	1	0	0	0	0	1	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	10	2	1	0	0	1	0	0	0	1	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	11	1	1	1	0	0	1	0	0	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	11	2	0	0	0	1	0	1	0	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	12	1	0	0	1	0	0	1	0	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone
2	12	2	1	0	0	1	1	0	0	0	55	Gen X	Male	Yes	No	Yes	Yes	7	Yes	Facebook Messen	Smartphone

Figure 7: Example of dummy coding and preparation of data for discrete choice analysis

3.8. Chapter Summary

This chapter discussed the methodology and methods employed in this research. A cross-sectional research design was used to investigate social media practices of age-diverse audiences and their preferences in relation to micro-influencer health and wellbeing message strategies. The stated preference method of a discrete choice experiment was a core element of the online survey. Discrete choice experiments are underpinned by a behavioural choice theory, namely, the RUT, which postulates that utility cannot be observed by researchers; however, a valid preference elicitation experiment can explain a proportion of the unobservable consumer utility (Louivere, 2001). Discrete choice was deemed appropriate as it enabled the examination of the micro-influencers' social media message strategies preferred by an age-diverse audience.

Data was collected through an online survey via the Qualtrics XM (2022) platform. The survey comprised seven sections which sought to understand the demographics of the respondent, their social media practices generally and in relation to micro-influencers, and their message strategy preferences. Message strategy preferences were determined through a full factorial design discrete choice experiment with 12 choice sets which comprised two attributes: message format, consisting of three levels, and message type, which consisted of four levels. There were 375 participants in the total sample; however, only 221 participants completed the discrete choice experiment and provided the data for the final discrete choice analysis.

Participants were recruited through four main strategies, including through micro-influencers who were asked to share with their followers, social media groups, the researcher's community and professional networks, and local community groups (offline).

Data analysis, including descriptive statistics (frequencies, means, cross-tabulations and chi-square tests), were conducted to understand sample characteristics and social media practices and to contextualise the study. Binary logistic regression was used to analyse the discrete choice experiment data to examine whether micro-influencer message strategy preferences vary based on age and social media platform preferences. The next chapter will present the survey results of this quantitative cross-sectional study.

Chapter Four: Empirical Results

A cross-sectional survey was designed to address the three research questions:

1) How do social media practices, generally and in relation to micro-influencers, vary among age-diverse audiences?
2) What social media message strategies do audiences of health and wellbeing micro-influencers prefer?
3) How do the audiences' preferences for message strategies vary based on social media platforms and among age-diverse audiences?

The survey was hosted on the online survey platform, Qualtrics XM (2022), and data was collected over a period of three and a half months, from December 2021 to mid-March 2022.

This chapter is organised into four sections:

- Section 1 describes the practices of the sample's social media use.
- Section 2 describes the sample's social media practices specific to micro-influencers.
- Section 3 will begin to outline the sample's preferences for social media platform, message format, and message type.
- Section 4 will present the results from the discrete choice experiment.

Cross-tabulations and chi-square analyses were conducted to understand the social media practices, generally and in relation to micro-influencers, of age-diverse audiences. In addressing the message strategy preferences of diverse age categories, both cross-tabulations and binary logistic regression were conducted. While the cross-tabulation investigations provide insight into the associations between age categories and message format and message type preferences, the binary logistic regression investigated preferences using a preference elicitation method – the discrete choice experiment data.

Prior to understanding preferences, it is important to understand the social media practices of an age-diverse audience. This addresses the first research question and is a key focus of this research.

This next section will report the results from the cross-tabulations and chi-square statistics that examined the associations between participants of diverse ages and their social media practices.

When conducting cross-tabulations with tables larger than 2 x 2, the chi-square was considered most appropriate as each observation was independent – that is, one observation per participant. Additionally, the researcher acknowledged the generally accepted condition whereby no more than 20% of expected cell counts are less than five, and where all individual expected cells counts are one or more (Cochran, 1954; Yates et al., 1999). In instances where cell violation is evident, this has been highlighted with a cautionary note below each chi-square table.

A conservative approach has been applied to all the following cross-tabulation/chi-square analyses by examining the potential for Type I errors. When the adjusted standardised residual is above the absolute value of 1.96 (MacDonald and Gardner, 2000), this would suggest that the cell count is significantly different from the null hypothesis, whereby there is no significant association. To address the issue of family-wise error and to account for Type I errors which can occur when performing a series of follow-up comparisons of standardised residuals in contingency table analysis (cross-tabulation analysis), Bonferroni Correction was performed. This involved converting the adjusted z-values to the chi-square values and then estimating the p-values. The p-values from the Bonferroni Correction are reported in results below. Additionally, whilst the Cramer's V, which measures the association between two variables, may show significance in some instances, accounting for the reduction of Type I errors often reduces the significance.

In the interpretation of effect sizes, Cohen's (1988) guidelines suggest that small effect size = .10, medium effect size = .30, and large effect size = .50 (Table 9). However, degrees of freedom can be considered in the interpretation (Cohen, 1988) of Cramer's V. The degrees of freedom are not from the chi-square test but are calculated using the minimum number of either the number of rows or number of columns and subtracting one from the lowest number (Stikker, 2022). For example, in a 4 x 3 contingency table, the lowest number is 3, and 1 is subtracted which equals 2 as the degrees of freedom.

Table 9: Interpretations for Cramer's V (Cohen, 1988)

df*	Negligible	Small	Medium	Large
1	0 < .10	.10 < .30	.30 < .50	.50 or more
2	0 < .07	.07 < .21	.21 < .35	.35 or more
3	0 < .06	.06 < .17	.17 < .29	.29 or more
4	0 < .05	.05 < .15	.15 < .29	.25 or more
5	0 < .05	.05 < .13	.13 < .22	.22 or more

4.1. Sample by Age Categories and Social Media Practices

The following section addresses RQ1: *How do social media practices, generally and in relation to micro-influencers, vary among age-diverse audiences?* To answer this research question and better understand the sample's social media use, participants were asked questions that related to how and when they use social media, and for what purpose. This section is organised by each question asked to participants in the survey.

4.1.1. Number of Social Media Accounts with Different Social Media Platforms

The screening process required participants to have at least one social media account to be eligible for the study. Participants were asked to select from a list provided, the social media platforms they had accounts with. Recoding the variable enabled the total number of social media accounts per participant to be recorded and reported. An important point to note is that participants may have more than one account with a social media platform (for example, three Instagram accounts, or two Twitter accounts); however, this question sought to understand the number of social media platforms participants had an account with, not the total number of social media accounts within each social media platform and across social media platforms.

4.1.1.1. Total Sample by Number of Social Media Accounts

Analysis of frequencies revealed that all 375 participants had at least one social media account, with 368 participants reporting that they had an account with more than one social media platform. The mean score (*M* = 6.81*, SD* = 2.512*)* suggests that on average participants had accounts with approximately seven different social media platforms.

4.1.1.2. Age Categories by Number of Social Media Accounts

When examining frequencies of participants' social media accounts by age categories, Gen Z participants had on average almost eight different social media accounts with different platforms (*M* = 7.80*, SD* = 2.313). Millennials (*M* = 6.97*, SD* = 2.397) and Gen X (*M* = 6.09*, SD* = 2.379) had the next highest, whilst the majority of Baby Boomers/Post War participants had the least number of social media platforms (*M* = 5.19*, SD* = 2.472). Whilst the mean does vary across age categories, the results do show that older age categories do have multiple social media accounts and further highlights the importance of understanding the practices of all age categories, including those who may not be considered digital natives.

The number of social media accounts were grouped into increments of five to allow for analysis of significant associations (Table 10).

Table 10: Chi-square results of age categories and number of social media accounts held by a participant

Number of Social Media Accounts	Age Categories (*n*)				χ^2	Cramer's V
	Gen Z	Millennials	Gen X	Baby Boomers/Post War		
1–5 Social Media Accounts	16 (-4.2)	30 (-1.7)	40 (3.6)	23 (3.9)	44.056***	.242
6–10 Social Media Accounts	84 (2.4)	92 (2.1)	47 (-3.0)	19 (-2.8)		
11+ Social Media Accounts	14 (3.1)	6 (-1.0)	4 (-0.9)	0 (-1.8)		

*Note. *** = p < .001. Adjusted standardised residuals appear in parentheses below category frequencies. One cell had an expected cell count less than 5; however, this is within acceptable limits.*

A chi-square test of independence was performed to examine the relationship between age categories and the number of social media accounts held by each participant. The relationship between these variables is significant, χ^2 (6, 375) = 44.056, $p < .001$, with a medium effect size, Cramer's V = .242.

Whilst there are a number of adjusted standardised residuals that suggest significant associations, when testing for Type I errors (Bonferroni Correction) not all associations remained significant.

However, post-hoc analysis did reveal that Gen Z were significantly less likely ($p < .001$) than expected to have fewer than five social media accounts, and significantly more likely ($p = .025$) than expected to have in excess of 11 social media accounts. Both Gen X ($p = .004$) and Baby Boomers/Post War ($p = .001$) were significantly more likely than the expected count to have fewer than five accounts with different social media platforms. Gen X were significantly less likely ($p = .038$) than expected to have between six and ten social media accounts than the total average.

4.1.2. Active Social Media User

Participants were also asked whether they consider themselves to be 'active users'. To help provide a point of reference for the term 'active user', a definition was provided in the survey. An active user was defined as *one who spends time on social media platforms and/or engages in direct exchanges with other social media users. Examples of direct exchanges include liking, sending messages, commenting, and sharing messages through photos, videos, or text.* This definition was adapted from Trifiro and Gerson (2019) and Verduyn et al. (2017). Although these two papers (along with a number of other studies, for example, Escobar-Viera et al., 2018; Khan, 2017; Valkenburg et al., 2022) focus on the differentiation between active and passive users, this question was asked to assist in identifying those who use their social media accounts in any way and those who have accounts they do not use at all.

4.1.2.1. Total Sample by Active Social Media User

Results revealed that the overwhelming majority (89.6%; *n* = 336) considered themselves active users, whilst 7.2% (*n* = 27) did not consider themselves active users, and 3.2% (*n* = 12) participants were unsure.

4.1.2.2. Age Categories by Active Social Media User

Cross-tabulation investigations into age categories by self-reported 'active user' status revealed that the majority of the participants within each age category (89.6%; *n* = 336) consider themselves to be active users. Table 11 below provides a full summary comparing age categories and whether a participant considered themself an active user.

Table 11: Chi-square results of age categories and active users

Active Social Media User	Age Categories (*n*)				χ^2	Cramer's V
	Gen Z	Millennials	Gen X	Baby Boomers/Post War		
Yes	107 (1.8)	113 (-0.6)	79 (-1.0)	37 (-0.3)	9.896	.115
No	5 (-1.4)	9 (-0.9)	11 (2.1)	2 (-0.6)		
Unsure	2 (-1.1)	6 (1.2)	1 (-1.3)	3 (1.5)		

Adjusted standardised residuals appear in parentheses below category frequencies. Caution when interpreting results is advised as more than 20% of cells (41.7%) had an expected count less than 5.

Investigation was conducted to determine if a significant association existed between age categories and whether or not participants consider themselves to be active social media users.

Chi-square analysis confirmed the relationship between the two variables was not significant χ^2 (6, 375) = 9.896, with examination of the cell counts showing the overwhelming majority in all age categories consider themselves to be active users.

4.1.3. Most Utilised Social Media Platforms

To enable deeper understanding of the most utilised social media platforms, participants were asked what social media platforms they are most active on.

4.1.3.1. Total Sample by Most Utilised Social Media Platforms

Results by the total sample revealed Instagram (30.1%; *n* = 113), Facebook (29.3%; *n* = 110), and Facebook Messenger (18.4%; *n* = 69) were the social media platforms that participants were most active on (see Table 12).

Table 12: Frequencies: social media platforms participants are most active on

Social Media Platform	*N*	%
Facebook	110	29.3
Instagram	113	30.1
Facebook Messenger	69	18.4
WhatsApp	23	6.1
Snapchat	13	3.5
TikTok	12	3.2
YouTube	12	3.2
LinkedIn	10	2.7
Twitter	6	1.6
Reddit	3	0.8
Pinterest	2	0.5
WeChat	2	0.5
Total	375	100

4.1.3.2. Age Categories by Most Utilised Social Media Platforms

When focusing on each age category and the platforms they are most active on (Table 13), results revealed that Gen Z (age 18–25 years) and Millennials (age 26–41 years) were most active on Instagram, and Gen X (age 42–57 years) and Baby Boomers/Post War (age 58–94 years) were most active on Facebook.

Table 13: Cross-tabulation of age categories and most utilised social media platforms

Social Media Platform	Age Categories (*n*)			
	Gen Z	Millennials	Gen X	Baby Boomers/Post War
Facebook (*n* = 110)	4	36	46	24
Facebook Messenger (*n* = 69)	31	17	15	6
Instagram (*n* = 113)	45	46	19	3
LinkedIn (*n* = 10)	0	4	3	3
Pinterest (*n* = 2)	1	0	0	1
Reddit (*n* = 3)	1	2	0	0
Snapchat (*n* = 13)	13	0	0	0
TikTok (*n* = 12)	10	2	0	0
Twitter (*n* = 6)	2	0	1	3
WeChat (*n* = 2)	0	1	1	0
WhatsApp (*n* = 23)	1	15	5	2
YouTube (*n* = 12)	6	5	1	0

To facilitate analysis of associations, the three most selected social media platforms were examined by age categories (Table 14), noting that participants were only able to select one option, that being the social media platform they were most active on.

Table 14: Chi-square results of age categories and top three most utilised social media platforms

Top 3 Social Media Platforms Most Active On	Age Categories (*n*)				χ^2	Cramer's V
	Gen Z	Millennials	Gen X	Baby Boomers/Post War		
Facebook	4 (-7.1)	36 (-0.3)	46 (4.3)	24 (4.4)	72.542***	.352
Facebook Messenger	31 (3.7)	17 (-1.9)	15 (-1.2)	6 (-0.8)		
Instagram	45 (3.8)	46 (2.0)	19 (-3.2)	3 (-3.7)		

*Note. *** = p < .001. Adjusted standardised residuals appear in parentheses below category frequencies.*

Chi-square analysis was conducted to establish if there were any significant differences between the age categories and the top three platforms that each age category is most active on (Table 14). The relationship between these variables is significant, χ^2 (6, 375) = 72.542, $p < .001$, with a large effect size, Cramer's V = .352.

Gen X ($p < .001$) and Baby Boomers/Post War ($p < .001$) age categories are more likely than expected by chance to be on Facebook and less likely than expected to be active on Instagram, $p = .015$ and $p = .003$ respectively. Gen Z were significantly more likely to be most active on Facebook Messenger ($p = .002$) and Instagram ($p = .002$) and less likely than expected to be active on Facebook ($p < .001$).

Whilst some of the adjusted standardised residuals in the remaining cells suggest statistically significant associations, analysis of family-wise error rate revealed these associations did not reach significance.

4.1.4. Technological Devices Used for Social Media

To provide insights into the type of devices participants use when accessing social media, participants were asked to indicate the device they use to most access their social media accounts.

4.1.4.1. Total Sample by Technological Devices Used for Social Media

The overwhelming majority of participants 91.7% (*n* = 344) access their social media account using their smartphone, with a further 2.9% (*n* = 11) indicating they use a laptop, 2.7% (*n* = 10) reporting they use a desktop computer, and 2.4% a tablet (*n* = 9). One individual indicated they most access their social media using their Smart Television. Interestingly, when drilling down to obtain further context, the participant who accesses their social media using their Smart Television selected YouTube as the platform they are most active on and so explains their device selection as YouTube is primarily used to share and view video content. Although this relates to only one individual in the sample, it does highlight that there are potential nuances in the way social media is consumed on different devices.

4.1.4.2. Age Categories by Technological Devices Used for Social Media

When reviewing frequencies of type of device used to most access social media by age categories (see Table 15 for full summary), whilst the overwhelming majority across all age categories used smartphones to access social media, there was a small number of participants, particularly Gen X (*n* = 4) and Baby Boomers/Post War (*n* = 6), who reported using tablet, laptop or a desktop computer. Given that over a third of Baby Boomers/Post War (35.7%) participants indicated that they use a tablet, laptop or a desktop computer, further studies are required to understand why these devices may be used by some Baby Boomers/Post War, to help ensure the information needs of those in these age categories are met and particularly to inform micro-influencer message strategies.

Table 15: Cross-tabulation of age categories and devices used to access social media

Device Used to Access Social Media	Age Categories (*n*)			
	Gen Z	Millennials	Gen X	Baby Boomers/ Post War
Smartphone	112	123	82	27
Tablet	0	0	4	5
Laptop	1	1	3	6
Desktop Computer	1	3	2	4
Smart Television	0	1	0	0

Chi-square analysis was conducted to examine any associations between age categories and the type of device used the most to access social media (Table 16). To facilitate meaningful analysis, laptop and desktop computer were combined into one device category as they were both considered computers, and given there was only one participant who indicated they used a Smart Television, this one case was removed from chi-square analysis.

Table 16: Chi-square results of age categories and devices used to access social media

Devices used to Access Social Media	Age Categories (n)				χ^2	Cramer's V
	Gen Z	Millennials	Gen X	Baby Boomers/Post War		
Smartphone	112 (3.0)	123 (2.5)	82 (-0.8)	27 (-7.0)	56.558***	.275
Tablet	0 (-2.0)	0 (-2.2)	4 (1.4)	5 (4.3)		
Computer	2 (-2.1)	4 (-1.5)	5 (-0.1)	10 (5.4)		

*Note. *** = p < .001. Adjusted standardised residuals appear in parentheses below category frequencies. Caution when interpreting results is advised, as more than 20% of cells (41.7%) had an expected count less than 5.*

Chi-square analysis revealed that the association between devices used to access social media and age categories was significant, χ^2 (6, 375) = 56.558, p < .001, with a medium effect size, Cramer's V = .275.

The Baby Boomers/Post War age category was significantly less likely to use a smartphone to access their social media (p < .001) than expected to occur by chance, and more likely to use a tablet (p < .001) or a computer to access social media (p < .001) than expected. Conversely, Gen Z were significantly more likely to access their social media on their smartphone (p = .038) than would be expected if the two variables were independent.

Although some of the remaining adjusted residuals suggest significant relationships, analysis of family-wise error rate, that is Bonferroni Correction, revealed these relationships did not reach significance.

4.1.5. Time Most Active on Social Media

To understand the time of day social media users are most active on social media, participants were asked to identify from a list of ten time periods when they are most active.

4.1.5.1. Total Sample by Time Most Active on Social Media

Participants are most active on social media in the mid-evening, between 8:01 pm and 10 pm (141 participants, 37.6%). Second and third most common times were in the late evening, between 10:01 pm and 12 am with 64 participants (17.1%), and in the early evening, between 6:01 pm and 8 pm with 61 participants (16.3%). Less common times participants were most active were in the late afternoon, between 4:01 pm and 6 pm with 24 people (6.4%), early morning between 6:01 am and 8 am, mid-morning from 8:01 am to 10 am, and late morning between 10:01 am and 12 pm, with 23 people (6.1%) in each. Ten people (2.7%) are most active in the mid-afternoon from 2:01 pm to 4 pm, 4 people (1.1%) are most active in the early afternoon between 12:01 pm and 2 pm, and 2 people (0.5%) are most active overnight from 12:01 am to 6 am.

4.1.5.2. Age Categories by Time Most Active on Social Media

When looking at age categories and the time participants were most active on social media, certain times across all age categories were more popular as stated above; however, there were some differences when comparing age categories (Table 17). As illustrated in Table 16, mid-evening (8:01 pm–10 pm) was the time all age categories (Gen Z, Millennials, Gen X, and Baby Boomers/Post War) were most active. When looking at other time periods, late evening (10:01 pm–12 am) saw younger generations, including Gen Z and Millennials, being more active on social media, whereas only one participant in the Baby Boomers/Post War generation was most active during this time. Results showed that there was no clear time where older participants tended to be most active. Responses from the Baby Boomers & Post War generations were spread across most time periods offered in the survey, the only exception being no participants in this age category selected overnight. Very few Gen Z reported the early or mid-morning as their most active time, whereas a number of respondents in the Millennials, Gen X, and Baby Boomers/Post War age categories reported being the most active on social media during this time. These results indicate that younger generations are more active in the evening, whereas middle-age and older generations (Millennials and older), while still being active in the evening, tend to also be active in the morning.

Table 17: Cross-tabulation of age categories and time most active on social media

Time Most Active on Social Media	Age Categories (*n*)			
	Gen Z (*n* = 114)	Millennials (*n* = 128)	Gen X (*n* = 91)	Baby Boomers/Post War (*n* = 42)
Early morning (*n* = 23)	1	9	8	5
Mid-morning (*n* = 23)	1	8	8	6
Late morning (*n* = 23)	8	4	6	5
Early afternoon (*n* = 4)	0	2	0	2

Mid-afternoon (*n* = 10)	4	2	2	2
Late afternoon (*n* = 24)	7	6	7	4
Early evening (*n* = 61)	24	17	12	8
Mid-evening (*n* = 141)	42	53	37	9
Late-evening (*n* = 64)	26	27	10	1
Overnight (*n* = 2)	1	0	1	0

To help establish if these associations were statistically significant, chi-square analysis was conducted (Table 18). Time periods were grouped together based on the general time of day (morning, afternoon, and night) to facilitate meaningful analysis.

Table 18: Chi-square results of age categories and time most active on social media

Time Most Active on Social Media	Age Categories (*n*)					
	Gen Z	Millennials	Gen X	Baby Boomers/Post War	χ^2	Cramer's V
Morning	10 (-3.2)	21 (-0.7)	22 (1.6)	16 (3.5)	27.694***	.192
Afternoon	11 (-0.2)	10 (-1.1)	9 (-0.1)	8 (2.0)		
Night	93 (2.9)	97 (1.3)	60 (-1.3)	18 (-4.4)		

*Note. *** = p < .001. Adjusted standardised residuals appear in parentheses below category frequencies. One cell had an expected cell count less than 5; however, this is within acceptable limits.*

Results showed that the relationship between time most active on social media and age categories was significant, χ^2 (6, 375) = 27.694, $p < .001$, with a small effect size, Cramer's V = .192.

Gen Z were less likely than expected to be active on social media in the morning ($p = .018$) and more likely than expected to be active at night (6:01 pm–6 am) ($p = .050$). Baby Boomers/Post War age category had the converse practice, whereby they were more likely

than the expected count to be most active in the morning (p = .006) and significantly less likely than expected to be active on social media at night (p < .001).

4.1.6. Frequency of Social Media Use

Participants were also asked how often they access their social media accounts. Participants were provided with eight levels of frequencies to select from.

4.1.6.1. Total Sample by Frequency of Social Media Use

Interestingly, but not surprising, due to the significant increase in social media uptake in recent years (Plantin & Punathambekar, 2019), a large number of people (37.9%; n = 142) access their social media constantly throughout the day – the highest level of frequency offered in the survey. Eighty-four participants, or 22.4% of the sample, access their social media about 5 to 10 times per day. This was followed by 75 participants (20.0%) accessing their social media more than 10 times per day, 60 participants (16.0%) about 1 to 4 times per day, and 14 participants (3.7%) several times a day.

4.1.6.2. Age Categories by Frequency of Social Media Use

A cross-tabulation of age and how often participants access their social media throughout the day revealed that more than half (52.6%; n = 60) of the Gen Z in the sample access their social media constantly throughout the day. This was also the case for Millennials with 40.6% (n = 52) of the age category constantly accessing their social media throughout the day. The Gen X category were relatively evenly spread across each of the categories offered in the survey, except for a small number (n = 5) who access their social media several times a week. This was consistent with the other age categories which also had small number of participants selecting the several times a week category (see Table 19). Baby Boomers/Post War participants typically access their social media less than the other generations, with more than half the participants in this age category (57.1%; n = 24) accessing their social media between 1 and 10 times per day.

Table 19: Chi-square results of age categories and frequency of social media access

Frequency of Social Media Access	Age Categories (*n*)					
	Gen Z	Millennials	Gen X	Baby Boomers/Post War	χ^2	Cramer's V
Constantly throughout the day	60 (3.9)	52 (0.8)	24 (-2.6)	6 (-3.3)		
More than 10 times per day	24 (0.3)	27 (0.4)	16 (-0.7)	8 (-0.2)		
About 5 – 10 times per day	26 (0.1)	25 (-1.0)	22 (0.5)	11 (0.6)	49.343***	.209
About 1 – 4 times per day	3 (-4.7)	20 (-0.1)	24 (3.1)	13 (2.8)		
Several times a week	1 (-1.9)	4 (-0.4)	5 (1.0)	4 (2.1)		

*Note. *** = p < .001. Adjusted standardised residuals appear in parentheses below category frequencies. Caution is advised as 20% of cells had an expected count less than 5; however, this remains within acceptable limits.*

Chi-square analysis revealed the association between frequency of social media access and age categories was significant, χ^2 (12, 375) = 49.343, $p < .001$, with a medium effect size, Cramer's V = .209. The frequency of access categories of 'constantly throughout the day' and '1 to 4 times a day' generated the most interesting results. Specifically, Gen Z were significantly more likely ($p = .002$) than expected to access social media constantly throughout the day in comparison to the total average. Conversely, Boomers/Post War were significantly less likely ($p = .017$) than expected to occur by chance to access social media constantly throughout the day, highlighting a potential difference in the social media practices of the two age categories.

Whilst Gen X age category were significantly more likely than expected to access their social media 1 to 4 times per day ($p = .038$), Gen Z were observed significantly less than expected to access social media only 1 to 4 times per day ($p < .001$).

4.1.7. Social Media Activities

To understand the activities for which social media are used, participants were asked to select all the options that applied to them from a list of 19 potential activities. Participants were asked to consider the past week of their social media use when answering the question.

4.1.7.1. Total Sample by Social Media Activities

Analysis of the activities that participants use social media for firstly showed that most of the participants (86.9%, *n* = 326) used social media for more than one activity. The mean number of activities participants selected was 4.74 (*SD = 3.132)*. When examining the type of activities more closely, one of the main reasons participants use social media is to *connect, communicate and stay in touch with people they know*, as selected by 303 participants (80.8%). *Staying up to date with current affairs and news* was also a popular reason with more than half the sample (53.3%, *n* = 200) using social media for this reason. *Passing the time* was the third main reason with 190 participants (50.7%). Next, 172 participants (45.9%) said they use social media to *watch videos*, and 155 participants (41.3%) said they use social media to *share photos, videos, and stories.*

4.1.7.2. Age Categories by Social Media Activities

A cross-tabulation analysis of age categories and social media activities was performed to understand the reasons why each generation use their social media. Analysis revealed that for the Gen Z age category, the top three activities include connecting, communicating, and staying in touch with people; passing the time; and watching videos. Similarly, the top three activities that Millennials use social media for include connecting, communicating, and staying in touch with people; passing the time; and staying updated with current affairs and news. The Gen X age category most use social media for connecting, communicating, and staying in touch with people; staying updated with current affairs and news; and passing the time. Baby Boomers/Post War use social media mostly to connect, communicate, and stay in touch with people; share photos, videos, and stories; find and connect with like-minded communities and interest groups; and stay updated with current affairs and news.

Results also showed that relative to the number of participants in each age category, when compared to Gen Z, participants in the Millennials and Gen X age categories also used social

media for business-related activities, including work-related networking, work-related research, and promoting a business.

As this analysis was conducted using frequencies and cross-tabulations within multiple response sets, chi-square tests were unable to be conducted. However, it is clearly evident that connecting, communicating, and staying in touch with people is a primary reason for using social media across all age categories (Table 20).

Table 20: Cross-tabulation of age categories and social media activities

Social Media Activities	Age Categories (*n*)			
	Gen Z	Millennials	Gen X	Baby Boomers/Post War
Stay updated with current affairs and news	59	70	54	17
Connect, communicate and stay in touch with people	107	93	66	37
Share photos, videos, stories	50	52	30	23
Meet new people	7	6	4	2
Pass the time	74	71	34	11
Watch videos	73	56	33	10
Find and connect with like-minded communities and interest groups	17	24	23	17
Discover and research new brands and products	28	26	17	2
Follow brands or organisations	26	22	16	2

Shop and make purchases	33	20	20	4
Play games	18	7	10	6
Organise or discover events	17	8	11	8
Follow celebrities and influencers	24	13	10	3
Inspiration and ideas	38	34	23	8
Read/write reviews	7	4	5	3
Promote a business	7	13	11	2
Customer service	1	6	6	2
Work-related networking	17	28	24	9
Work-related research	10	19	18	6

4.2. Followers of Micro-influencers by Social Media User Practices

Following the general social media practices questions, study participants were then asked a series of questions to understand their practices regarding digital micro-influencers. For the purpose of the online survey and this research, micro-influencers are defined as *digital influencers, also known as social media influencers, who have between 10,000 and 100,000 followers on a social media platform. Due to their smaller audience, micro-influencers typically have a greater capacity to connect and interact with their followers on a more*

intimate and personal level and can be considered to be more authentic and accessible to their audience. Participants were provided with this definition to ensure consistency among interpretation of the questions and the subsequent results.

4.2.1. Followers of Micro-influencers

Firstly, participants were asked whether they follow micro-influencers on social media.

4.2.1.1. Total Sample by Followers of Micro-influencers

When asked whether participants followed a micro-influencer, results from 373 responses revealed that 198 participants (52.8%) follow micro-influencers, 126 participants (33.6%) do not follow micro-influencers, and 49 participants (13.1%) were unsure whether they followed micro-influencers or not. Two participants did not answer this question or continue the survey (incomplete 0.5%).

4.2.1.2. Age Categories by Followers of Micro-influencers

Cross-tabulation analysis of followers of micro-influencers by age categories (Table 21) showed that more than half of Gen Z (64.6%) and Millennials (62.2%) follow micro-influencers. In comparison, less than half of Gen X (37.4%) and Baby Boomers & Post War (28.6%) follow micro-influencers.

To help establish if these differences were statistically significant, chi-square analysis was conducted (Table 21). Analysis revealed the association between followers of micro-influencers and age categories was significant, χ^2 (6, 373) = 49.383, $p < .001$, with a medium effect size, Cramer's V = .241.

Participants in the Gen Z age category were observed significantly more than expected to follow a micro-influencer ($p = .040$) than not, whilst Gen X ($p = .007$) and Baby Boomers/Post War ($p = .009$) were observed significantly less to respond yes and significantly more likely to respond no to following a micro-influencer, $p = .003$, $p = .001$ respectively.

Table 21: Chi-square results of followers of micro-influencers by age categories

Follow a Micro-influencer	Age Categories (*n*)				χ^2	Cramer's V
	Gen Z	Millennials	Gen X	Baby Boomers/Post War		
Yes	73 (2.9)	79 (2.5)	34 (-3.5)	12 (-3.4)	43.382***	.241
No	20 (-4.3)	35 (-1.8)	45 (3.6)	26 (4.1)		
Unsure	20 (1.7)	13 (-1.2)	12 (0.0)	4 (-0.7)		

*Note. *** = p < .001. Adjusted standardised residuals appear in parentheses below category frequencies. Caution is advised as 8.3% of cells had an expected count less than 5; however, this remains within acceptable limits.*

4.2.2. Non-followers of Micro-influencers

For participants who responded *no* or *unsure* to the question about whether they follow a micro-influencer, they were then asked whether, based on the definition of micro-influencer provided to them, they would consider following a micro-influencer in the future.

4.2.2.1. Total Sample by Non-followers of Micro-influencers

There was a total of 175 participants who answered *no* or *unsure* as to whether they follow micro-influencers. Out of these 175 participants, 51 (29.1%, 13.6% of total sample) said they would consider following a micro-influencer in the future, 84 (48.0%, 22.4% of total sample) said they would not consider following a micro-influencer in the future, 39 (22.3%; 10.4% of total sample) were unsure, and one person did not complete the question.

4.2.2.2. Age Categories by Non-followers of Micro-influencers

Participants who answered *no* or *unsure* as to whether they follow micro-influencers were then asked if they would consider following a micro-influencer in the future.

To establish whether there were any significant associations between age categories and their likelihood to follow a micro-influencer in the future, chi-square analysis was conducted (Table 22) and revealed a significant relationship, χ^2 (6, 174) = 13.566, $p < .05$, with a small effect size, Cramer's V = .197.

Specifically, there was a significant negative association between the Baby Boomers/Post War age category and the likelihood of following a micro-influencer in the future (p = .030), suggesting that this age category is less likely than expected to a follow micro-influencer in the future.

Table 22: Chi-square results of likely to follow micro-influencer in the future and age categories

Likely to Follow a Micro-influencer in the Future	Age Categories (*n*)				χ^2	Cramer's V
	Gen Z	Millennials	Gen X	Baby Boomers/Post War		
Yes	17 (2.1)	14 (0.1)	17 (0.1)	3 (-2.6)	13.566*	.197
No	14 (-1.9)	24 (0.4)	24 (-1.1)	22 (3.0)		
Unsure	9 (0.0)	9 (-0.6)	16 (1.2)	5 (-0.8)		

*Note. * = p < .05. Adjusted standardised residuals appear in parentheses below category frequencies.*

4.2.3. Reasons for Following Micro-influencers

The participants who were existing followers of micro-influencers were asked a series of questions about their social media practices in relation to micro-influencers. In the first question, participants were provided with a list of possible reasons for following a micro-influencer and were asked to select which reasons applied to them.

4.2.3.1. Total Sample by Reasons for Following Micro-influencers

Out of the 198 participants who follow micro-influencers, 193 participants answered the questions that examined the practices of followers of micro-influencers. Analysis revealed that the main reason for following a micro-influencer was *inspiration and ideas* (71.5%, *n* = 138). This was followed closely by *relaxing and entertaining content* (63.2% of participants, *n* = 122). The third reason participants followed micro-influencers was for *reviews and opinions* (37.3% of participants, *n* = 72). The fourth reason was *brand and product information* (29.0% of participants, n = 56), and fifth was *discounts and promotions* (13.5% of participants, *n* = 26). Some participants also provided other reasons for why they follow

micro-influencers: some micro-influencers are people they know, general interest pages, and to support small businesses.

4.2.3.2. Age Categories by Reasons for Following Micro-influencers

A cross-tabulation of age categories and reasons for following micro-influencers was conducted to understand the main reasons social media users follow micro-influencers (Table 23). *Inspiration and ideas* and *relaxing and entertaining content* were the two main reasons that all age categories (Gen Z, Millennials, Gen X, and Baby Boomers/Post War) follow micro-influencers. This analysis used frequencies and cross-tabulations within multiple response sets to analyse the data and consequently statistical tests to determine significant associations were unable to be conducted.

Table 23: Cross-tabulation of age categories by reasons for following micro-influencers

Reasons for following micro-influencers	Age Categories			
	Gen Z	Millennials	Gen X	Baby Boomers/Post War
Discounts & Promotions	12	10	3	1
Giveaways & Competitions	3	6	2	0
Inspiration & Ideas	50	54	26	8
Brand & Product Information	20	24	11	1
Reviews & Opinions	28	29	11	4
Relaxing & Entertaining Content	49	46	19	8
Companionship	3	3	3	0

4.2.4. Social Media Platforms Used to Follow Micro-influencers

The corresponding question for this section asked participants which social media platforms they use to follow micro-influencers.

4.2.4.1. Total Sample by Social Media Platforms Used to Follow Micro-influencers

When examining the platforms that audiences use when following micro-influencers, most participants across the total sample selected Instagram (85.5%, *n* = 165). Facebook was the second most selected social media platform (31.6%, *n* = 61), YouTube was a close third (30.6%, *n* = 59), and the fourth most selected social media platform was TikTok (21.8%, *n* = 42). Note that participants were able to select as many platforms as they required.

4.2.4.2. Age Categories by Social Media Platforms Used to Follow Micro-influencers

Investigation of age categories by the social media platforms audiences use when following micro-influencers (Table 24) showed that for three of the four age categories (Gen Z, Millennials, and Gen X), Instagram, which is classified as a media sharing network (Foreman, 2017), was the most selected social media platform used. It is important to note, however, that a large number of participants in the Gen Z age category also indicated that they use TikTok (*n* = 27) and YouTube (*n* = 27), both considered media sharing networks, to follow micro-influencers.

For Millennials, the second and third most selected social media platforms for following micro-influencers were YouTube (media sharing network) and Facebook, which is classified as a social network (Foreman, 2017).

The second most used platform for following micro-influencers for Gen X was Facebook, whilst for the Baby Boomers/Post War age category, Facebook was the most used social media platform when following micro-influencers. This suggests that the younger age categories use media sharing networks to follow micro-influencers. In comparison, it appears that the older age category uses social networks to follow micro-influencers. This fundamental difference in the nature of the most used social media platform for each of the two age categories suggest that there are potential differences in the way they like to view messages from micro-influencers.

Table 24: Cross-tabulation of age categories by social media platforms used to follow micro-influencers

Social Media Platforms Used to Follow Micro-influencers	Age Categories			
	Gen Z	Millennials	Gen X	Baby Boomers/Post War
Facebook	7	28	19	7
Facebook Messenger	0	1	0	2
Instagram	65	64	32	4
LinkedIn	2	7	5	1
Pinterest	1	3	4	0
Skype	0	1	0	0
Snapchat	2	0	0	0
TikTok	27	8	5	2
Tumblr	1	0	0	0
Twitch	0	1	0	0
Twitter	4	4	1	0
WeChat	0	0	1	0
WhatsApp	0	1	0	1
YouTube	27	23	5	4

When asked if participants follow the same micro-influencer on more than one social media platform, of the 193 participants who follow a micro-influencer and answered this question, 97 participants (50.3%) said they do follow micro-influencers on more than one platform, and 96 (49.7%) indicated they only follow a micro-influencer on the one platform. Further analysis revealed no significant associations between the two variables, χ^2 (6, 193) = 1.008 (Table 25).

Table 25: Chi-square results of age categories by follow micro-influencer on more than one social media platform

Follow Micro-influencer on more than one platform	Age Categories					
	Gen Z	Millennials	Gen X	Baby Boomers/ Post War	χ^2	Cramer's V
Follow a micro-influencer on more than one platform	38 (0.7)	36 (-0.6)	18 (0.3)	5 (-0.6)	1.008	.072
Do not follow a micro-influencer on more than one platform	33 (-0.7)	40 (0.6)	16 (-0.3)	7 (0.6)		

Adjusted standardised residuals appear in parentheses below category frequencies.

4.3. Followers of Micro-influencers by Social Media Message Strategy Preferences

This section focuses specifically on the social media message strategy preferences of those who follow micro-influencers or who would follow micro-influencers in the future.

4.3.1. Followers of Micro-influencers by Social Media Platform Preferences

This first focus in this section is the social media platform preferences of those who follow micro-influencers or who would follow micro-influencers in the future.

4.3.1.1. Total Followers of Micro-influencers by Social Media Platform Preferences

Frequencies were examined to better understand participants' social media platform preferences when viewing messages shared by micro-influencers (Table 26). Participants were only able to select their *most preferred* – that is, one option. Consistent with the result discussed in section 4.2.4.1., where Instagram was the *most used* social media platform to follow a micro-influencer across the total sample, the results in the table below reveal Instagram is the *most preferred* social media platform across the total sample. This finding

highlights that there may be a link between the two constructs of social media platform most used and social media platform preference.

Table 26: Frequencies of preferred social media platform

Social Media Platform	N	% (Valid Responses)
Facebook	34	14.1
Facebook Messenger	9	3.7
Instagram	154	63.9
LinkedIn	3	1.2
TikTok	14	5.8
Twitter	6	2.5
WeChat	1	0.4
WhatsApp	3	1.2
YouTube	16	6.6
Other	1	0.4
Total	241	100

4.3.1.2. Followers of Micro-influencers by Age Categories and Social Media Platform Preferences

To determine if social media platform preferences vary by age categories when viewing messages by micro-influencers, a cross-tabulation analysis was conducted (Table 27). Results revealed that across three age categories (Gen Z, Millennials, and Gen X), Instagram was the most preferred platform to view messages by micro-influencers. For the Baby Boomers/Post War age category, Facebook was the most preferred platform.

Table 27: Cross-tabulation of age categories by preferred social media platform

Social Media Platform Preferences	Age Categories			
	Gen Z	Millennials	Gen X	Baby Boomers/Post War
Facebook	4	13	12	5
Facebook Messenger	2	2	2	3
Instagram	61	63	28	2
LinkedIn	0	1	1	1
TikTok	10	3	1	0
Twitter	3	2	1	0
WeChat	0	0	1	0
WhatsApp	0	1	1	1
YouTube	7	4	2	3

To help ensure meaningful conclusions can be drawn from the data, social media platforms were grouped into types of social media platforms for further chi-square analysis. Foreman (2017) identified ten types of social media platform categories. When applying these categories, the social media platforms most selected by participants across the total sample were in two out of the ten types of social media platforms (Table 28). The two types are *Social Networks*, which include Facebook, Facebook Messenger, LinkedIn, Twitter, WeChat, and WhatsApp; and *Media Sharing Networks*, which include Instagram, YouTube, and TikTok.

Table 28: Chi-square results of age categories by preferred social media platform

Social Media Platform Type	Age Categories				χ^2	Cramer's V
	Gen Z	Millennials	Gen X	Baby Boomers/Post War		
Social Networks	9 (-3.6)	19 (-0.6)	18 (2.5)	10 (4.1)	29.065***	.348
Media Sharing Networks	78 (3.6)	70 (0.6)	31 (-2.5)	5 (-4.1)		

*Note. *** = p < .001. Adjusted standardised residuals appear in parentheses below category frequencies. One cell had an expected cell count less than 5; however, this is within acceptable limits.*

Results revealed a significant relationship between social media platform type and age category, χ^2 (3, 240) = 13.566, p < .001, with a medium effect size, Cramer's V = .348.

Results showed that Gen Z were significantly more likely than the expected count to prefer media sharing networks (p = .003) such as Instagram and TikTok, whereas Baby Boomers/Post War were significantly more likely than expected to prefer social networks (p < .001) such as Facebook.

4.3.2. Followers of Micro-influencers by Social Media Message Format Preferences

This section examines the responses about message format preferences when viewing messages shared by micro-influencers. Of the initial 375 participants, 236 provided a response to this question.

4.3.2.1. Total Followers of Micro-influencers by General Message Format Preference

In the first instance, participants were asked about their most preferred message format in a general sense. Results by the total sample revealed that *video* (n = 121) was the most preferred message format. *Picture* was selected by 73 participants as their most preferred message format, and *text* (n = 42) was the least preferred message format when viewing messages shared by micro-influencers.

4.3.2.2. Total Followers of Micro-influencers by Age Categories and General Message Format Preference

Cross-tabulation analysis to determine association between message format preference and age categories showed *video* to be the message format most preferred by each age category when viewing messages by micro-influencers. However, chi-square statistics revealed no significant associations between the variable message format, and the age category variable, χ^2 (6, 236) = 6.526 (Table 29).

Table 29: Chi-square results of age categories by preferred social media message format

Message Format	Age Categories				χ^2	Cramer's V
	Gen Z	Millennials	Gen X	Baby Boomers/Post War		
Text	11 (-1.4)	15 (-0.2)	11 (1.0)	5 (1.6)	6.526	.118
Picture	27 (0.3)	25 (-0.6)	18 (1.0)	3 (-0.9)		
Video	46 (0.8)	48 (0.8)	20 (-1.6)	7 (-0.4)		

Adjusted standardised residuals appear in parentheses below category frequencies. Caution is advised when interpreting results given that, whilst within acceptable limits, 16.7% of cells had an expected count less than 5.

4.3.2.3. Total Followers of Micro-influencers by Message Format Preference for Most Preferred Social Media Platform

Within the survey, participants' preferred social media platform was piped into this question to establish their social media message format preference in the context of their preferred social media platform. When comparing results from the previous section which asked for participants' message format preferences in a general sense, results showed that even when thinking about their preferred social media platform, *video* remained the most preferred message format when viewing micro-influencers' messages (*n* = 103). This was followed by *picture* (*n* = 99). The least preferred message format was *text* (*n* = 34).

4.3.2.4. Followers of Micro-influencers by Age Categories and Message Format Preference for Most Preferred Social Media Platform

Preferences for message format within the context of participants' preferred social media platform was then examined by age categories (Table 30). *Video* was the most preferred message format for Millennials, whilst most of Gen Z preferred *picture* message format. Gen X equally preferred *video* and *picture*, whilst Baby Boomers/Post War participants equally preferred *video* and *text*.

Chi-square statistics did not reveal any significant association, χ^2 (6, 236) = 11.094, p = .086; Cramer's V = .153.

Whilst typically post-hoc tests are not conducted when the chi-square value does not reach significance, given that the adjusted standardised residual in the Baby Boomers/Post War and Text cell was greater the 1.96, significance fell just outside of p = 0.05, and to account for a possible Type II error, a Bonferroni Correction post-hoc test was conducted. Whilst falling just within significance level, results revealed that Baby Boomers/Post War were significantly more likely than expected to prefer the *text* message format when thinking about their preferred social media platform (p = .042). Given the nature of this result, caution is advised. This is an area worth investigating further in future studies.

Table 30: Chi-square results of age categories by preferred social media message format when thinking of social media platform preference

Message Format	Age Categories				χ^2	Cramer's V
	Gen Z	Millennials	Gen X	Baby Boomers/Post War		
Text	10 (-0.8)	9 (-1.4)	9 (0.9)	6 (2.9)	11.094	.153
Picture	38 (0.8)	38 (0.3)	20 (-0.2)	3 (-1.8)		
Video	36 (-0.2)	41 (0.7)	20 (-0.4)	6 (-0.3)		

Adjusted standardised residuals appear in parentheses below category frequencies. Caution is advised as 8.3% of cells had an expected count less than 5; however, this remains within acceptable limits.

4.3.3. Followers of Micro-influencers by Social Media Message Type Preferences

This section examines responses about message type preferences when viewing messages shared by micro-influencers. Of the initial 375 participants, 230 provided a response to this question.

4.3.3.1. Total Followers of Micro-influencers by General Message Type Preference

In the first instance, participants were asked about their preferred message type from a general perspective. Results revealed that *informative* message type (*n* = 129) was the most preferred when viewing health and wellbeing messages shared by micro-influencers. This was followed by *emotional or relatable* message type (*n* = 46), and *interactive* message type (*n* = 42). *Promotional* (*n* = 13) was the message type least selected as a preference across all recorded responses.

4.3.3.2. Followers of Micro-influencers by Age Categories and General Message Type Preference

When looking at whether different age categories prefer different message types, cross-tabulation analysis revealed all age categories preferred *informative* messages shared by micro-influencers. A chi-square test of independence was conducted to determine any significant associations between the variable *social media message type preference* and the variable *age categories*; however, no significant associations were evident (Table 31).

Table 31: Chi-square results of age categories and preferred social media message type

Message Type	Age Category				χ^2	Cramer's V
	Gen Z	Millennials	Gen X	Baby Boomers/Post War		
Informative	40 (-1.8)	51 (1.1)	27 (0.0)	11 (1.4)	9.355	.116
Promotional	7 (1.4)	2 (-1.6)	4 (0.9)	0 (-1.0)		
Interactive	18 (1.0)	15 (-0.1)	6 (-1.2)	3 (0.2)		
Emotional or Relatable	18 (0.5)	16 (-0.3)	11 (0.6)	1 (-1.3)		

Adjusted standardised residuals appear in parentheses below category frequencies.

4.3.3.3. Total Followers of Micro-influencers by Message Type Preference for Most Preferred Social Media Platform

Within the survey, participants' preferred social media platform was piped into this question to establish their social media message type preference in the context of their preferred social media platform. When comparing results from the previous section which asked for participants' message type preferences in a general sense, results showed *informative* remained the most preferred message type (*n* = 118), followed by *emotional or relatable* (*n* = 52). Third most preferred was *interactive* (*n* = 44), and the least preferred message type was *promotional* (*n* = 16).

4.3.3.4. Followers of Micro-influencers by Age Categories and Message Type Preference for Most Preferred Social Media Platform

Preference for message type within the context of participants' preferred social media platform was then examined by age categories. *Informative* was the most preferred message type for all age categories (see Table 32). Chi-square statistics did not reveal any significant associations. However, given a number of adjusted standardised residuals were above 1.96, a Bonferroni Correction post-hoc test was conducted. This confirmed no significant associations between message type preferences when considering social media platform preferences variable and age categories. This finding warrants further investigation given that, whilst the most preferred message type across age categories was *informative*, the media richness theory suggests that the *interactive* message type is likely to generate a higher level of engagement (Moran et al. 2019). As such, further exploration is warranted in future studies.

Table 32: Chi-square results of age categories by preferred social media message type when thinking of social media platform preference

Message Type	Age Categories				χ^2	Cramer's V
	Gen Z	Millennials	Gen X	Baby Boomers/Post War		
Informative	37 (-1.5)	45 (0.5)	27 (0.8)	9 (0.7)	12.547	.135
Promotional	4 (-1.0)	7 (0.6)	5 (1.1)	0 (-1.1)		
Interactive	17 (0.4)	19 (1.0)	4 (-2.1)	4 (0.8)		
Emotional or Relatable	25 (2.0)	13 (-2.0)	12 (0.4)	2 (-0.9)		

Adjusted standardised residuals appear in parentheses below category frequencies.

4.3.4. Followers of Micro-influencers by Impact of Varying Topics on Message Strategy Preferences

Upon completion of the discrete choice experiment in the survey, participants were asked whether their message strategy preferences were likely to differ depending on the topic of the message being shared.

4.3.4.1. Total Followers of Micro-influencers by Impact of Varying Topics on Message Strategy Preferences

When examining message strategy preferences by total recorded responses, results from 218 participants revealed that for 39.9% of participants (*n* = 87) message strategy preferences would differ depending on the topic of the message, whilst 21.1% (*n* = 46) said the topic of the message would not affect their message strategy preferences, and 39% (*n* = 85) were unsure.

4.3.4.2. Followers of Micro-influencers by Age Category and Impact of Varying Topics on Message Strategy Preferences

When examining if there were any significant associations between age categories and if message strategy preferences were likely to differ based on message topic, cross-tabulations and chi-square statistics revealed no significant associations (Table 33).

Table 33: Chi-square results of age categories by preferred message strategy (MS) differ depending on message topic

MS Preferences Likely to Differ Based on Topic	Age Categories				χ^2	Cramer's V
	Gen Z	Millennials	Gen X	Baby Boomers/Post War		
Yes	34 (0.7)	30 (-0.8)	15 (-0.9)	8 (1.6)	9.633	.149
No	21 (1.5)	14 (-1.1)	8 (-0.5)	3 (0.2)		
Unsure	24 (-2.0)	38 (1.7)	21 (1.3)	2 (-1.8)		

Adjusted standardised residuals appear in parentheses below category frequencies.

4.4. Discrete Choice Experiment

This final section of the results chapter will present the results from the discrete choice experiment, including the relationships between:

- message format and audience message strategy preferences and the moderating variables of age and participants' social media platform preference
- message type and audience message strategy preferences and the moderating variables of age and participants' social media platform preference.

4.4.1. Analysis of Discrete Choice Experiment Data

The statistical software, Stata (StataCorp, 2021), was used to analyse the discrete choice data. To enable coding to be used for statistical analysis and to determine the preference selected by participant for each choice set, dummy coding was used. The value of '1' indicated that a participant selected the choice set alternative as their preference, and the value of '0' indicated that they did not select the variable as their preference. Due to the binary nature of the responses, the analysis performed was binary logistic regression, specifically using the logit model.

In line with McFadden's (1973) RUT, the conditional logit model was used to estimate the message strategy preferences of the respondents (Ryan et al., 2008; Turner & Coote, 2017), whether the two attributes, message format and message type, were statistically significant predictors of participants' preferences, and whether age and social media platforms moderate the effect of message format and message type on preference. In Stata, the *cLogit* command was used to execute this logit model.

One level of each attribute was used as the baseline or reference category for the analysis. For the attribute 'message format', *text* was used as the baseline. Text was selected as the baseline because the literature has identified that text has lower media richness in comparison to more visual message formats such as video (Moran et al., 2019). For the attribute 'message type', *promotional* was used as the baseline. Promotional was selected because the literature has identified this message type as being one of the least effective message types (Leung et al., 2017).

A greater preference for an attribute level compared to the baseline level is indicated by a positive and larger coefficient value (Kotnowski et al., 2015; Oluboyede et al., 2019). When an attribute level has a negative coefficient value this suggests that participants would prefer not to move from the reference level.

To eliminate collinearity, when running the *cLogit* function, Stata automatically removes a predictor variable if it is highly associated with another predictor variable.

4.4.2. Discrete Choice Experiment Results

Table 34 presents Model 1 of the logistic regression which consists of all attributes included in the experiment.

The Wald chi-square of 331.95 indicates that the model as a whole fits significantly better than a model with no predictors.

Table 34: Model 1 – Attributes only

Variables	Coef.	*SE*	*p*-value
Message Format			
Picture	0.854	0.096	0.000
Video	0.886	0.118	0.000
Text (Omitted)	0		
Message Type			
Informative	1.820	0.129	0.000
Emotional or Relatable	1.326	0.114	0.000
Interactive	1.111	0.102	0.000
Promotional (Omitted)	0		

4.4.2.1. Model 2 Interaction Effects: Message Format and Message Types by Age Categories

Table 35 presents Model 2 of the logistic regression which consists of all interaction effects for age categories and message formats and message types. As per the analysis of the chi-square statistics in previous sections, the Baby Boomers and Post War age categories were merged due to small numbers in the Post War age category and to allow meaningful conclusions to be drawn. The Gen Z age category (selected automatically by Stata software) was the baseline category for the age category variable.

The results of Model 2 revealed that for only one attribute out of the two – message type – age categories was a moderating variable of message strategy preferences when viewing messages shared by micro-influencers. Therefore, hypothesis 2_a, which suggested that audience age moderates the relationship between message types and audiences' message strategy preferences, is supported; however, hypothesis 1_a, which suggested that audience age moderates the relationship between message formats and audiences' message strategy preferences, is not supported.

Model 2 Interaction Effects: Message Format by Age Categories

This model revealed that the message formats picture (b = 0.718, p < 0.001) and video (b = 0.859, p < 0.001) in comparison to the reference category text, were statistically significant and had a positive effect on preference.

For the picture level, the Baby Boomers/Post War coefficient was negative (b = -0.272) in comparison to the Gen Z age category (see Table 34 for all coefficients) whereas, for the Millennials age category (b = 0.359) and the Gen X age category (b = 0.107), the coefficient was positive. Whilst this suggests that compared to Gen Z, Millennials and Gen X are more likely to prefer picture and Baby Boomers/Post War are less likely to prefer picture, these effects were not statistically significant.

For video, the coefficient of Millennials was positive (b = 0.405) in comparison to Gen Z, however for Gen X (b = -0.262) and Baby Boomers/Post War (b = -0.371), the coefficients were negative. Although this suggests that, in comparison to Gen Z, Gen X and Baby Boomers/Post War are less likely to prefer video, the interactions were not significant.

Whilst the insights into non-significant results are of interest, given the interaction effects of message format by age categories did not reach significance in Model 2, caution is advised when drawing any conclusions about how preferences for message format vary by age categories.

Model 2 Interaction Effects: Message Type by Age Categories

With regard to message type, Model 2 showed that the message types informative (b = 1.962, p < 0.001), emotional or relatable (b = 1.798, p < 0.001), and interactive (b = 1.293, p < 0.001) in comparison to the reference category promotional, were statistically significant and had a positive effect on preference.

For the message type level, informative, both the coefficients of the interaction between Millennials (*b* = -0.313), and the interaction between Gen X (*b* = -0.287) did not obtain significance. However, the interaction between informative and Baby Boomers/Post War was positive and significant, (*p* = 0.035). This indicates that the Baby Boomers/Post War age category had a strengthening effect on informative message types on preference and therefore they were more likely to prefer informative messages than the Gen Z age category.

For the level, emotional or relatable, the coefficients for the three age categories, Millennials (*b* = -0.518), Gen X (*b* = -0.891), and Baby Boomers/Post War (*b* = -1.007), were negative. This suggests that each of these three age categories had a weakening effect on the positive effect of emotional or relatable message types on preference and that they were less likely to prefer the emotional or relatable message type to Gen Z. However, only two of the interactions reached significance – the interaction of emotional or relatable and Millennials (*p* = 0.049), and the interaction between emotional or relatable and Gen X (*p* = 0.005). The interaction between emotional or relatable and Baby Boomers/Post War was not significant (*p* = 0.065).

For the level, interactive, the coefficient of Millennials was negative (*b* = -0.215) but insignificant. The coefficient of the Gen X age category was also negative (*b* = -0.654), however, did reach significance (*p* = 0.016). This indicated a weakening effect of the positive effect of interactive message types on preference and therefore this age group was less likely to prefer interactive messages. For the Baby Boomers/Post War age category, the coefficient was positive but not significant.

Table 35: Model 2 – interaction effects: message formats and message types x age category

Variables	Coef.	*SE*	*p*-value
Picture	0.718	0.162	0.000
Picture x Age Category			
Picture x Millennials	0.359	0.222	0.106
Picture x Gen X	0.107	0.282	0.704
Picture x Baby Boomers/Post War	-0.272	0.297	0.361
Video	0.817	0.185	0.000
Video x Age Category			
Video x Millennials	0.405	0.269	0.132
Video x Gen X	-0.262	0.338	0.438

Variables	Coef.	*SE*	*p*-value
Video x Baby Boomers/Post War	-0.371	0.410	0.366
Text (Omitted)	0		
Text x Age Category (Omitted)	0		
Text x Millennials (Omitted)	0		
Text x Gen X (Omitted)	0		
Text x Baby Boomers/Post War (Omitted)	0		
Informative	1.958	0.242	0.000
Informative x Age Category			
Informative x Millennials	-0.313	0.312	0.316
Informative x Gen X	-0.287	0.356	0.420
Informative x Baby Boomers/Post War	1.067	0.506	0.035*
Emotional or Relatable	1.779	0.195	0.000
Emotional or Relatable x Age Category			
Emotional or Relatable x Millennials	-0.518	0.263	0.049*
Emotional or Relatable x Gen X	-0.891	0.314	0.005**
Emotional or Relatable x Baby Boomers/Post War	-1.007	0.545	0.065†
Interactive	1.308	0.198	0.000
Interactive x Age Category			
Interactive x Millennials	-0.215	0.250	0.390
Interactive x Gen X	-0.654	0.273	0.016*
Interactive x Baby Boomers/Post War	0.522	0.492	0.289
Promotional (Omitted)	0		
Promotional x Age Category (Omitted)	0		
Promotional x Millennials (Omitted)	0		
Promotional x Gen X (Omitted)	0		
Promotional x Baby Boomers/Post War (Omitted)	0		

*† p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001*

4.4.2.2. Model 3 Interaction Effects: Message Format and Message Types by Social Media Platform Preferences

Table 36 presents Model 3 of the logistic regression which consists of all interaction effects for social media platform (by platform preferences) and message formats and message types. Social media platforms were grouped into types of social media platforms to enable meaningful analysis to be conducted. The three types of social media platforms are Media

Sharing Networks, which include platforms such as Instagram, YouTube, and TikTok; Social Networks, which include platforms such as Facebook and LinkedIn; and Direct Messaging Platforms, which consist of social media platforms such as Facebook Messenger and WhatsApp. Media Sharing Networks (selected automatically by Stata software) was the baseline category for the Type of Social Media Platform variable.

Results revealed that for only one attribute out of the two – message type – social media platform preferences was a moderating variable of message strategy preferences when viewing health and wellbeing messages shared by micro-influencers. Therefore, hypothesis 2_b, which suggested social media platform preference moderates the relationship between message types and audiences' message strategy preferences, is supported; however, hypothesis 1_b, which suggested that social media platform preference moderates the relationship between message formats and audiences' message strategy preferences, is not supported.

Model 3 Interaction Effects: Message Format by Social Media Platform Preferences

Model 3 revealed that the message formats picture (b = 0.959, p < 0.001) and video (b = 0.988, p < 0.001) in comparison to the reference category text, were statistically significant and had a positive effect on preference.

For the picture level, the coefficients (see Table 35 for all coefficients) for both Social Networks (b = -0.404) and Direct Messaging Platforms (b = -0.551) were negative indicating that the preference for picture is less likely on social media platforms that are not Media Sharing Networks (which is the reference category). These interactions, however, did not obtain significance and as such no conclusions can be drawn in relation to this finding.

Similarly for video, the coefficients of both Social Networks (b = -0.545) and Direct Messaging Platforms (b = -0.041) were negative and not significant. Whilst this further suggests Media Sharing Networks were the preferred social media platforms for video message formats, conclusions cannot be drawn given results did not reach significance.

Model 3 Interaction Effects: Message Type by Social Media Platform Preferences

In regard to message type, Model 3 showed the message types informative (b = 1.806, p < 0.001), emotional or relatable (b = 1.415, p < 0.001), and interactive (b = 1.087, p < 0.001) in

comparison to the reference category promotional, were statistically significant and had a positive effect on preference.

For the message type level, informative, the coefficient of Social Networks was positive (*b* = 0.127), and the coefficient of Direct Messaging Platforms was negative (*b* = -0.036). Both these interactions did not reach statistical significance and so, no conclusions can be drawn.

For the level, emotional or relatable, the coefficient of Direct Messaging Platforms was negative (*b* = -0.997) and statistically significant (*p* = 0.042) suggesting that this type of social media had a weakening effect of the positive effect of emotional or relatable messages on preference. However, whilst the coefficient of Social Networks was also negative (*b* = -0.153), the interaction was not significant.

For the message type level, interactive, whilst the coefficient of Social Networks was positive (*b* = 0.225), it did not obtain significance. Conversely, the coefficient of Direct Messaging Platforms was negative (*b* = -0.224), however, was also not significant.

Table 36: Model 3 – interaction effects: message formats and message types x social media platforms (by platform preferences)

Variables	Coef.	*SE*	*p*-value
Picture	0.959	0.111	0.000
Picture x SM Platform Preference			
Picture x Social Networks	-0.404	0.252	0.109
Picture x Direct Messaging Platforms	-0.551	0.291	0.058†
Video	0.988	0.135	0.000
Video x SM Platform Preference			
Video x Social Networks	-0.545	0.330	0.099†
Video x Direct Messaging Platforms	-0.041	0.263	0.875
Text (Omitted)	0		
Text x SM Platform Preference (Omitted)			
Text x Social Networks (Omitted)	0		
Text x Direct Messaging Platforms (Omitted)	0		
Informative	1.806	0.143	0.000
Informative x SM Platform Preference			
Informative x Social Networks	0.127	0.355	0.721
Informative x Direct Messaging Platforms	-0.036	0.624	0.955

Variables	Coef.	*SE*	*p*-value
Emotional or Relatable	1.415	0.125	0.000
Emotional or Relatable x SM Platform Preference			
Emotional or Relatable x Social Networks	-0.153	0.330	0.643
Emotional or Relatable x Direct Messaging Platforms	-0.997	0.490	0.042*
Interactive	1.087	0.114	0.000
Interactive x SM Platform Preference			
Interactive x Social Networks	0.225	0.281	0.423
Interactive x Direct Messaging Platforms	-0.224	0.596	0.706
Promotional (Omitted)	0		
Promotional x SM Platform Preference (Omitted)			
Promotional x Social Networks (Omitted)	0		
Promotional x Direct Messaging Platforms (Omitted)	0		

*† p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001*

Although there are results in this discrete choice experiment which did not reach significance, they may be of interest for future studies in this field.

4.4.2.3. Comparison of Discrete Choice Models

Model 1 was the base model and included all the attributes within the discrete choice experiment. This model shows that both message format (picture, video, and text) and message type (informative, emotional or relatable, interactive, and promotional), are all predictors of the dependent variable, preference of health and wellbeing message strategy shared by micro-influencers.

Model 2 and Model 3 consist of all interaction effects for message format and message type by age category, and social media platform (by platform preference), respectively, on the dependent variable, preference of health and wellbeing message strategy shared by micro-influencers. These models show that social media platform (by platform preference) was

not as significant of a predictor for message strategy preference in comparison to age categories.

Model 3 had only one significant value, that being the interaction of emotional or relatable with direct messaging platforms (p = 0.042). While this does suggest participants are less likely to prefer emotional or relatable messages on direct messaging platforms, the model overall suggests social media platform may not be a significant factor of preference. The interaction of message strategy and age categories on the other hand, which is shown in Model 2, is shown to be a stronger predictor of preference, specifically for message type, as evidenced by a number of significant interactions. For example, the significant interaction of informative and Baby Boomers/Post War (p = 0.035) showed a strengthening effect of informative message types on preference. This suggests that the age category of the audience, and their message type preference, may be more of a consideration for micro-influencers sharing health and wellbeing messages when they are wanting to appeal to certain ages, or across age categories.

Although the results of the discrete choice experiment show that social media platform (by platform preference) did not impact preference significantly for the overall sample, significant results from the chi-square analysis (Table 28) showed that different age categories do prefer certain types of social media platforms. Therefore, in order to better align with the media needs of different ages, tailoring message strategies to certain social media platforms may still be beneficial when targeting or directing a message to a specific age category.

Chapter Five: Discussion and Conclusion

The previous chapter presented the results of the data analysis. Chapter Five will discuss the results aligned with the three research questions, noting once again that, given the non-probability nature of the sample, findings are specific to the study sample and cannot be generalised to the wider population. The chapter will conclude with the theoretical and industry implications, an outline of the strengths and limitations of the study, and considerations for future research. The chapter will bring together results from the cross-tabulations, and binary logistic regression to provide insight into the preferences of an age-diverse audience in relation to micro-influencer message strategies, specifically when sharing messages about health and wellbeing.

Micro-influencers are increasingly being recognised as credible topic experts (Alassani & Goretz, 2019) who can engage more intimately with their audiences (Gómez, 2019; Hatton, 2018), and who can act as a marketing intermediary between a brand and consumers (De Veirman et al., 2017). Given the broadening of age-diverse audiences on social media (Park et al., 2021; Pew Research Center, 2019), and that digital inclusion is a key priority to ensure that people in the community have every opportunity to age well (Office for Ageing Well, 2019), the study focus is particularly relevant.

As such, the present study has addressed three key questions:

1) How do social media practices, generally and in relation to micro-influencers, vary among age-diverse audiences?
2) What social media message strategies do audiences of health and wellbeing micro-influencers prefer?
3) How do the audiences' preferences for message strategies vary based on social media platforms and among age-diverse audiences?

This chapter is organised into seven main sections:

- Section 1 will address RQ1 and will discuss the social media practices of an age-diverse audience, including practices specific to micro-influencers, by age categories. The key findings of RQ1 are summarised at the start of this section.

- Section 2 will address RQ2 in relation to the social media message strategy preferences of an age-diverse audience. For the purposes of this study, message strategy is inclusive of social media platform, message format and message type, and comprises a combination of the three elements. The key findings of RQ2 are summarised at the start of this section.
- Section 3 will address RQ3, providing insights into the preferences for message strategies by age categories and social media platforms.
- Sections 4 and 5 highlight the theoretical contributions and industry and social implications of the research.
- Section 6 discusses the strengths and limitations of the study.
- Section 7 will conclude the chapter and will discuss potential directions for future research.

For ease of reference, the age categories are provided in the table below.

Table 5: Age categories by generation

AGES	YEAR BORN	AGE CATEGORY
25 and under	1997–2012	Gen Z
26–41	1981–1996	Millennials
42–57	1965–1980	Gen X
58–76	1946–1964	Baby Boomers
77–94	1928–1945	Post War

The results reported herein are drawn from a non-probability sample and whilst findings cannot be generalised to a population, they have provided insights regarding the social media practices of age-diverse audiences in this sample. Further, although the findings suggest a number of possible considerations for micro-influencers wanting to share health and wellbeing messages with specific age categories or across age categories, future studies that employ probability/random sampling are needed to verify the findings from the current study.

5.1. Social Media Practices of Age-Diverse Audiences (RQ1)

Before delving into the social media preferences of an age-diverse audience, it was important to first understand and gain a perspective of some of the social media practices

of the age-diverse audience sampled for this study. This provided a foundation for the interpretation of the subsequent discrete choice experiment and the critical context for any conclusions drawn. It was also useful to inform the practical application of micro-influencer marketing to age-diverse audiences and how to formulate an effective and tailored message strategy that aligns with the information needs of age-diverse audiences. As such, this section addresses RQ1: *How do social media practices, generally and in relation to micro-influencers, vary among age-diverse audiences?* This section outlines age categories by the following areas of investigation: the number of social media accounts, active user status, the most utilised social media platforms, technological devices used for social media, time of day most active on social media, frequency of social media use, and social media activities. The results discussed in this section provide a holistic view of the way age-diverse audiences engage with social media.

5.1.1. RQ1 Summary of Key Findings

Consistent with the literature, one of the primary reasons for age-diverse audiences to use social media is to connect, communicate, and stay in touch with others (Arora et al., 2018; Eastman et al., 2021). Whilst all age categories consider themselves to be active users on social media, the frequency of daily access did vary, with Gen Z more likely to access social media constantly throughout the day. This suggests that there may be less need for micro-influencers to consider the time of day when delivering health and wellbeing messaging to Gen Z. However, a novel finding is that Baby Boomers/Post War and Gen X indicated that they were more likely to access social media in the morning. Therefore, a more considered strategy regarding timing of messaging may be required with Baby Boomers/Post War and Gen X. Further, Gen Z, Millennials, and Gen X age categories are most active on *media sharing networks* such as Instagram, whereas Baby Boomers/Post War age categories were most active on *social networks* such as Facebook. It may be useful then, for micro-influencers to consider the type of social media platform in their message strategy, particularly when sharing health and wellbeing messages to age-diverse audiences.

There are nuances regarding devices used by age-diverse audiences when accessing social media accounts. Understanding these subtle differences can help inform the message strategies by leveraging the platform-specific and device-specific features and functionality

to facilitate the communication effectiveness of a message (Carlson & Zmud, 1999) and to create an optimal user experience when viewing health and wellbeing messages.

For those utilising micro-influencer marketing, an important and relatively novel finding is that Gen Z is most likely to follow micro-influencers, which suggests that when delivering health and wellbeing messages, there is potential for greater likelihood of reaching Gen Z through micro-influencer marketing. However, participants in the Baby Boomers/Post War generation, who at the time of the survey were not following micro-influencers, indicated that they would not follow micro-influencers in the future. Therefore, if delivering health and wellbeing messages to Baby Boomers/Post War age category, alternatives to micro-influencers may be worth considering. Importantly, however, it will be critical to ensure that the decision to follow or not follow a micro-influencer is not impacted by any misconceptions related to micro-influencers or influencers in general.

When examining the reason for following micro-influencers, *inspiration and ideas* was reported as a key motivation for following micro-influencers across all age categories, with *relaxation and entertainment* also reported frequently as a motive. This suggests that micro-influencers would benefit by using these next level message type insights to inform their message strategies and to more closely align with the information needs of age-diverse audiences (Daft & Lengel, 1983). Larger studies, however, are needed to validate these findings.

5.1.2. Number of Social Media Accounts

When reviewing the number of social media accounts by age categories, the youngest age category, Gen Z, was less likely to have fewer than five social media accounts and significantly more likely to have a larger number of social media accounts across a wide range of social media platforms, reporting more than 11 social media accounts. Whilst this result is not altogether unexpected, it does reinforce that for micro-influencers, and for those who utilise micro-influencer marketing, there are a large number of social media platform options for delivering messaging to this age category. As such, it is likely that this age category is easier to reach on social media. Additionally, there is increased opportunity for micro-influencers to connect with their Gen Z audiences across a wider range of social

media platforms, further maximising the potential reach of marketing messages related to health and wellbeing.

When reviewing the two oldest age categories, Gen X and Baby Boomers/Post War, the results revealed that participants were more likely to have fewer than five accounts with different social media platforms. This suggests that micro-influencers who are delivering messages about health and wellbeing to older age categories need to do so across a more targeted number of social media platforms.

Although there was no significant association between the age category of Millennials and the number of social media accounts, examination of frequencies showed that most participants in this age category reported having between 6 and 10 social media accounts with different social media platforms. This suggests that micro-influencers delivering messaging to this age category should consider a wider range of social media platforms; however, an understanding of Millennials' preferred platforms may increase the likelihood of ensuring the messaging reaches the intended audience (refer to section 4.3.1.).

Consistent with the literature (e.g., Shahbaznezhad et al., 2021), the findings of the current study suggest that there is merit in implementing a multi-platform social media approach, in which the same message is shared among a number of different social media platforms, and utilises the functions and features of each social media platform. This aligns with media richness theory which posits that different variations in media used to communicate (that is, social media platforms) can impact the way information is consumed by audiences and may be an important consideration for micro-influencers when sharing health and wellbeing messages to audiences of diverse ages.

5.1.3. Active Social Media Use

To help minimise misinterpretation of 'active user', the term was defined within the survey as '*one who spends time on social media platforms and/or engages in direct exchanges with other social media users. Examples of direct exchanges include liking, sending messages, commenting, and sharing messages through photos, videos, or text*'.

Interestingly, when examining participants' self-reporting of their active social media use, there was no significant relationship observed in this sample of age categories. Further,

whilst it may be commonly assumed that Gen Z are the most active social media users (Pew Research Center, 2019), the results from this study suggest that this assumption is unfounded, as the majority of all participants across all age categories consider themselves active on social media. Therefore, micro-influencers and those who utilise micro-influencer marketing need to ensure that no assumptions are made regarding age categories and the extent of their social media use. Social media is a legitimate avenue for delivering health and wellbeing messages to age-diverse audiences.

5.1.4. Social Media Platforms Most Active

With regard to which social media platform they were most active on, participants were able to select from 16 options; however, due to the spread of the responses, significant relationships were only examined by the three most selected social media platforms across all age categories: Facebook, Facebook Messenger, and Instagram. Consistent with industry reports (Auxier & Anderson, 2021; Dixon, 2022; Vogels, 2019) and the academic literature (Eastman et al., 2021), results from this study showed a significant association between age categories and social media platforms that users are most active on. Older age categories (Gen X, Baby Boomers/Post War) are more likely to be most active on Facebook and less likely to be active on Instagram. This suggests that if micro-influencers want to share messages with those in the Baby Boomers/Post War generations, Facebook would be a more effective avenue to share those messages and less focus should be placed on Instagram. Conversely, if micro-influencers want to communicate with younger people (Gen Z), Instagram should be utilised more with less focus on using Facebook. Whilst there were no significant associations between Millennials and the social media platforms that they are most active on, frequencies revealed that this age category are most active on Instagram and Facebook and therefore these platforms should be the focus when targeting health and wellbeing messages to the Millennial generation. This has implications for micro-influencers sharing health and wellbeing messages that have broad age appeal, in that a multi-platform approach to sharing health and wellbeing messages to age-diverse audiences is likely to be the most successful.

5.1.5. Device Used to Access Social Media

Insights into the type of devices that age-diverse audiences use to access social media can help inform the way health and wellbeing marketing messages are delivered by micro-influencers. Previous studies have highlighted how the access methods of social media platforms by users can impact usage behaviour and how messages and information are shared on these platforms (Heinrichs et al., 2011). In the current study, respondents were provided with six types of technological devices, namely, smartphone, tablet, laptop, desktop computer, smart television and wearables. A significant association was evident between age categories and devices used to access social media: Baby Boomers/Post War generations are most likely to use their computers or tablets to access their social media and less likely to use smartphones, whilst Gen Z typically use their smartphone to access their social media accounts.

The results suggest that if micro-influencers are targeting a specific age category on social media, they should not only consider the platforms being used by their target age category, but also the main devices being used. Further, messaging should be tailored to devices by leveraging the available features of the social media platforms by device type, which then enhances the user experience and creates the best environment for micro-influencers or micro-influencer marketing to meet objectives. The findings further reiterate the importance of understanding how different age categories access social media by device in order to better tailor messages to one age category or across all age categories by leveraging the features of those devices.

5.1.6. Time of Day Most Active on Social Media

To understand the time of day different age categories were most active on social media, respondents were given several timeframes to select from. Once again, results were spread across most of the options provided. Therefore, to enable meaningful conclusions to be drawn from the data, the responses were grouped into broader timeframes – morning, afternoon, and night. The significant relationship between age categories and the time of day they are most active on social media indicate that certain age categories are on social media at certain times of the day. This finding has implications for micro-influencers and those who utilise micro-influencer marketing, as it suggests that there are certain times of

the day when certain age categories are more likely to be reached. For example, if a micro-influencer is targeting the young Gen Z age category, morning is not the best time to share messages as Gen Z are more likely to be active at night and so messages may be missed by this age category if shared during this time. In contrast, the Baby Boomers/Post War age category, who are more likely to be active in the morning, would benefit from targeted messages between 6 am and 12 pm, as results suggest that this is the most effective time to reach this age category.

5.1.7. Frequency of Social Media Use

The frequency of social media use by age categories was significant, suggesting that depending on age, social media audiences will access their social media accounts with greater or less frequency. Auxier and Anderson (2021) reported findings consistent with this research; however, their study focused on frequency of access on specific social media platforms, such as Facebook and Instagram. This study considered social media platforms in general and found that Baby Boomers/Post War and Gen X are not on social media constantly so micro-influencers wanting to target these age categories should focus on the time of day they are most active to be able to effectively target and communicate with them.

Conversely, Gen Z reported that they constantly access their social media throughout the day and so, from a micro-influencer's perspective, the time of day to reach this age category does not require as much consideration as there is a high likelihood of reaching this age category at any time. Although the majority of Millennials indicated that they also constantly access their social media throughout the day, significance levels were not reached so no conclusions can be drawn about this age category and how often they access their social media throughout the day. With that said, frequencies revealed that Millennials vary in how often they access social media throughout the day. Although 40.6% of Millennial participants stated that they use social media constantly throughout the day, the responses from the remaining respondents in the age category were spread among the other options provided, which ranged from several times a week to more than 10 times per day.

5.1.8. Social Media Activities

To better understand the number and type of activities that an age-diverse audience use social media for, participants were asked to select the activities they used social media for in the past week. Results revealed that participants generally nominated a small number of activities (*M* = 4.74; *SD* = 3.132) for which they use social media. This result suggests that social media tends to serve quite specific purposes, with the overwhelming majority (80.8%; *n* = 303) of the total sample specifying that one of the main reasons they use social media is to *connect, communicate and stay in touch with people they know*. This highlights that social media has an important purpose in enabling social relationships, which is a key aspect of positive ageing. Participants share aspects of their lives through media-rich formats, including sharing *photos, videos, and stories* (41.3%; *n* = 155). This notion of connection being one of if not the key activity in which social media is used for is strongly supported by the literature (Arora et al., 2018; Baker, 2012; Eastman et al., 2021; Rainie, 2018; Yuan et al., 2016). This study extends Eastman et al.'s (2021) findings that focused on two out of the four generations – Millennials and Baby Boomers. The results of this study show that Gen Z and Gen X also report connecting and communicating as the main reason for using social media. The importance of addressing online connection is also highlighted by government bodies who consider it one of the essential aspects of living and participating in today's society (Office for Ageing Well, 2019). During the COVID-19 pandemic, for example, the reliance on online technologies like social media accelerated and provided people globally the opportunity to continue connecting, communicating and staying in touch with each other (Pew Research Center, 2020).

The findings also suggest that social media has a role to play in the dissemination of information, with 53.3% (*n* = 200) of participants across the total sample reporting that they use social media to *stay up to date with current affairs and news*. Given this result and that it can be challenging to decipher credible versus untrustworthy news in online environments (Australian Communications and Media Authority, 2020), exploring how social media platforms can better support and promote credible news stories warrants further investigations. There is also an opportunity, therefore, for social media platforms to be leveraged as a channel for sharing important health and wellbeing and public health news updates for age-diverse audiences. How best to deliver information will be examined

in more detail in section 5.2. which will discuss preferred social media platform, message format and message type. However, it is worth noting that with almost half of the participants (45.9%; *n* = 172) indicating that they use social media to *watch videos*, how to better utilise video as a message format for communicating important health messages on social media is worthy of further consideration in future studies.

5.1.9. Followers and Non-followers of Micro-influencers

Micro-influencers are recognised as providing an optimal combination of engagement and reach (Farivar et al., 2021). Their smaller number of followers, 10,000 to 100, 000 (Alassani & Göretz, 2019; Gómez, 2019), enables them to connect and interact on a more intimate and personal level (Farivar et al., 2021; Olsen & Sandholmen, 2019). Yet whilst the literature proposes this from a broad audience perspective, this study aimed to establish if there were any significant associations between age categories and followers of micro-influencers, to inform if micro-influencer marketing related to health and wellbeing is relevant for age-diverse audiences.

A significant relationship was evident, with Gen Z more likely than not to follow micro-influencers, and Baby Boomers/Post War less likely to report they follow a micro-influencer. Even when examining their likelihood of following a micro-influencer in the future, there was a significant negative association with the Baby Boomers/Post War age category, suggesting that this age category is unlikely to follow a micro-influencer in the future. There is a need to further explore this result, given that there may be several reasons for this negative association, including the potential unfamiliarity with the term/concept of micro-influencer or existing negative preconceptions of influencer marketing. This is particularly in light of results which showed that Baby Boomers/Post War (40.5%; *n* = 17) reported using social media to find and connect with like-minded communities and interest groups, which is a potential advantage of engaging with micro-influencers. Importantly too, it will be critical for future research to examine, possibly in a longitudinal study, if results remain anchored to the generation rather than shift with age. For example, will Gen Z as they age still follow micro-influencers or will their intention and practice of following micro-influencers reduce as they get older.

5.1.10. Motives for Following Micro-influencers

When examining motives for following micro-influencers, *inspiration and ideas* (71.5%, *n* = 138) was the most selected reason across all the age categories. This suggests that audiences of micro-influencers are receptive to being motivated by new information and ways of doing and being, which could include new health and wellbeing practices. There is an opportunity then, for micro-influencer marketing to inspire age-diverse audiences with new ways of engaging in healthy practices. Another key reason for following micro-influencers was the relaxation and entertainment provided (63.2% of participants, *n* = 122). Therefore, when drilling down to the next level of message type, that is, beyond the rational, transactional, interactional and transformational, there may be merit in future research to consider how relaxation and entertainment can be incorporated into micro-influencer marketing to align with audiences' motivation and information needs (Lengel & Daft, 1984). In Lee et al.'s (2022) study on motives for following influencers, authenticity, consumerism, creative inspiration, and envy were the four main motives and suggest some parallels to the findings in this current study. Whilst two of the four motives supported the findings, there were two contrasting aspects that differentiate the studies. Whilst Lee et al. (2022) focused on influencers generally (mega, macro, micro, etc., influencers) and investigated the motives of 18–29-year-old Instagram users, this study focuses specifically on micro-influencers and sought to understand the motivations for diverse age categories.

5.1.11. Social Media Platforms Used to Follow Micro-influencers

Micro-influencers are increasingly present on a range of social media platforms (Campbell, 2022; Soto-Vásquez & Jimenez, 2022). Media sharing networks such as Instagram, TikTok and YouTube were generally the most used types of social media platforms for engaging with micro-influencers for Gen Z, Millennials, and Gen X age categories. Whilst the Baby Boomers/Post War age category used the social network platform Facebook to engage with micro-influencers. The existing literature (both academic and industry) partially supports these findings, as Instagram was determined as the most used social media platform for influencer marketing (Bentley et al., 2021; Campbell, 2022) followed by TikTok, Facebook, YouTube, and Twitter (Campbell, 2022). This study extends these findings by identifying which age categories are using these different social media platforms to follow micro-influencers and provides further context in relation to where micro-influencers may have

the greatest opportunity to communicate and share messaging with the different age categories. This insight can further be used to inform, tailor, and target health and wellbeing messages to age-diverse audiences.

When participants were asked if they follow micro-influencers on more than one platform, results were inconclusive, with an almost equal split across the yes and no response options for each age category. Future research to explore reasons for responses is warranted to inform micro-influencer marketing strategies.

Findings have revealed that age categories do vary in how they use social media. Understanding differences in social media practices across age categories is important as it can help support age-friendly policy priorities of digital inclusion (Office for Health and Wellbeing, 2019). For example, when delivering messages to older age categories, namely Baby Boomers/Post War and Gen X, findings from the current study revealed that delivering messages on a more targeted number of social media platforms, especially Facebook, may be more effective as these age categories are most active on this platform and tend to be active on fewer social media platforms. This insight can inform how micro-influencers in the health and wellbeing space can better tailor and target messages to audiences of diverse ages to maximise reach and impact.

5.2. Social Media Message Strategy Preferences of Age-diverse Audience (RQ2)

The second research question asked: *What social media message strategies do audiences of health and wellbeing micro-influencers prefer?*

This question was divided into three separate sub-questions to address each aspect of a message strategy, namely, the social media platform used to host or share the message (RQ2a), the format of the message (RQ2b), and the type of message (RQ2c). The following sub-sections focus on each aspect of message strategies. Section 5.2.1. will discuss preferences for social media platforms among age-diverse audiences, section 5.2.2. will discuss the message format preferences of an age-diverse audience, and section 5.2.3. will discuss the message type preferences of an age-diverse audience.

5.2.1. RQ2 Summary of Key Findings

Findings revealed that media rich messages formats, particularly video, were most preferred across all age categories when viewing messages shared by micro-influencers, whilst message formats with a low level of media richness, particularly text, were least preferred across all ages. When reviewing message type, informative messages were the most preferred across all age categories when viewing messages shared by micro-influencers, with promotional the least preferred across all ages.

Whilst industry reports indicate that Facebook is the most used social media platform in the world (We Are Social, 2022b), findings from this current study extend our understanding by firstly, examining preferences of an age-diverse audience (who do, or would, follow micro-influencers) by two categories of social media platforms: media sharing networks, and social networks, and secondly, examining any potential differences by age categories. When viewing micro-influencer messages, Baby Boomers/Post War most preferred social networks, particularly Facebook; conversely, Gen Z, Millennials and Gen X preferred media sharing networks, particularly Instagram. For micro-influencers, this study highlights some of the nuances that may be important to consider when delivering messages to an age-diverse audience.

5.2.2. Social Media Platform Preferences of an Age-diverse Audience (RQ2a)

RQ2a: What social media platforms do audiences of health and wellbeing micro-influencers prefer?

In section 5.1.3, and as part of addressing RQ1, findings discussed the social media platform that participants were most active on. Given that no assumptions can be made that the social media platform that participants are most active on is the same as the social media platform they most prefer, this section explores the possibly related but distinctly different construct of preference. That is, what social media platform do participants prefer when viewing messages shared by micro-influencers. Importantly then, this study has differentiated between social media platforms participants are most active on and those that participants most prefer.

Across the total sample, results revealed that Instagram was the most preferred platform to view messages shared by micro-influencers. However, when delving into preferences by age categories, Gen Z, Millennials and Gen X all preferred Instagram, whilst the Baby Boomers/Post War age category most preferred Facebook. To better understand this difference, it helps to consider the fundamental features of each of these social media platforms. Instagram is considered a media sharing network which provides a place to share or consume media, for example, photos, and videos (both long and short form content). Conversely, Facebook, which is preferred by Baby Boomers/Post War, is considered a social network platform that predominantly aims to aid users to communicate and connect with social circles, either through messaging or through media.

In line with media richness theory, aligning users' information needs with their preferred type of media can generate more effective communication (Daft & Lengel, 1986). The findings regarding preferences also align with the findings related to the different social media activities nominated by each of the different age categories. For example, in section 4.1.7.2., Baby Boomers/Post War age category reported that they used social media mostly to connect, communicate, and stay in touch with people; share photos, videos, and stories; find and connect with like-minded communities and interest groups; and stay updated with current affairs and news. This aligns with their preference for social network platforms, especially Facebook, and is supported by the literature (Fisher, 2020; Shane-Simpson et al., 2018). Conversely, whilst connecting, communicating, and staying in touch with people was a key social media practice for Gen Z, one of their top three uses of social media was to pass the time by watching videos on media sharing networks. Worth noting is that young adults find video format easy to learn from (Lim et al., 2022) and consider Instagram as a source of inspiration for health and wellness (Lim et al., 2022).

This suggests that media sharing networks like Instagram are more likely to be the most effective social media platforms for micro-influencers to deliver messages to Gen Z, Millennials and Gen X. Given that the primary purpose of media sharing platforms is to share media, micro-influencers should place greater emphasis on the visual message formats, such as photos and videos, to deliver the messaging and inspire healthy and positive wellbeing practices. On the other hand, if delivering messages to Baby Boomers and Post War age categories, then micro-influencers need to consider social network platforms

such as Facebook and craft their messaging in a way that connects users both to the information and to the community.

While media richness theory emphasises message format and message type considerations, findings from the current study suggest that these considerations may be tightly linked to the social media platform on which the message is shared, as platforms can determine the level of media richness. For example, if a micro-influencer is using a social media platform such as TikTok to share a message, the message will have a high level of media richness as TikTok is a media sharing network where video is the main message format used.

5.2.3. Social Media Message Format Preferences of an Age-diverse Audience (RQ2b)

RQ2b: What social media message formats do audiences of health and wellbeing micro-influencers prefer?

Given that written texts, pictures, and videos are considered the most important message formats for influencers when disseminating their messages (Enke & Borchers, 2019), this current study explored participants' message format preferences.

The literature suggests that the type of message format can have implications for the impact of messages shared (Leung et al., 2017), with studies showing significant variations in the level of engagement, depending on the format of the content and the platform on which the content is delivered (Moran et al. 2019; Shahbaznezhad et al. 2021). A high level of richness is more likely to result in higher engagement (Moran et al. 2019). This highlights that along with the type of social media platform, message format is a critical consideration for those who use social media and micro-influencers to convey messages to an age-diverse audience.

Rich forms of media such as video can convey a greater level of emotion through characteristics such as movement and music and will result in a higher level of audience engagement (Shahbaznezhad et al., 2021). It is not surprising then, that when participants in the current study were asked about their preferred message format generally, they nominated video as their most preferred social media message format when viewing messages shared by micro-influencers. The finding is in line with results from the current study which also showed that almost half (45.9%) of participants indicated that they use

social media to watch videos. Findings also revealed that when thinking about message format generally, text was the least preferred format. This is consistent with the literature which proposes that text, which is considered to have low media richness, is less effective than media-rich formats such as video and pictures (Leung et al., 2017).

If, as suggested by Moran et al. (2019), the richness of the format determines the engagement level of the communication, with higher levels of richness more likely to result in higher engagement, then micro-influencers sharing messages on social media platforms should consider messaging with a high level of media richness in order to maximise engagement and the visibility of the content.

However, this research highlights a need to consider how the age of the audience, and the nature of the message itself, will influence not only engagement but the power of the communication. This raises some interesting dilemmas for those crafting social media messages when thinking about age-diverse audiences. One message strategy may not align with the communication needs of audiences of all ages and when the message is associated with health and wellbeing, to be most effective, the message format and message type skewed simply to greater media richness may not be the best approach. Instead, it may be more beneficial to concentrate on the foundational elements of media richness theory which focus on aligning media to the information needs of audiences (Daft & Lengel, 1983), when constructing a message. This means that preferences for different types of messages relating to the purpose of the message may also be a factor for age-diverse audiences and is explored further in the next section. Further understanding of preferences by age also adds insight to this observation as discussed in section 5.3.2.

5.2.4. Social Media Message Type Preferences of an Age-diverse Audience (RQ2c)

RQ2c: What social media message types do audiences of health and wellbeing micro-influencers prefer?

Message type refers to the style and structure of the message delivered via a message format on a social media platform (Leung et al., 2017; Shahbaznezhad et al., 2021). The literature suggests that there are four social media message types: rational (functional, and educational), transactional (promotion/remunerative), transformational (emotional, brand resonance, experiential, and social-cause related), and interactional (current events,

personal, brand community, and customer relation) (Chae 2020; Kim et al., 2021; Leung et al., 2017; Shahbaznezhad et al., 2021; Tafesse & Wien, 2018). For the purposes of the survey, these terms were simplified to provide more descriptive labelling for participants. Rational/informative messages are those that provide information and resources to educate consumers about a brand, product and/or service. Transactional/promotional messages are promotional or sales driven. Transformational/emotional or relatable messages are those that are emotional or communicate a social cause, whilst interactional/interactive messages seek to involve, and interact with, audiences in order to build relationships with them (Chae 2020; Kim et al., 2021; Leung et al., 2017; Shahbaznezhad et al., 2021; Tafesse & Wien, 2018).

Interestingly, the literature suggests that messages that are interactive in nature typically have a higher level of media richness and attract a higher level of engagement (Shahbaznezhad et al., 2021). The current study found that from a general perspective and across the total sample, participants' most preferred message type was informative when receiving messages from micro-influencers. This highlights that in the context of messages shared by micro-influencers, audiences in the first instance prefer to be informed and educated.

The finding from this current study, which showed that participants' least preferred messages are promotional messages, is aligned with the literature which posits that promotional messages are one of the least effective message types (Leung et al.,2017). This suggests that for micro-influencers the overarching intention in messages should focus on educating audiences rather than engaging in influencer marketing aimed to promote or sell a product or service. However, influencers have diverse missions and objectives, which may include marketing to generate revenue/sales, so incorporating an element of education within a promotional message may help to extend the reach, impact and engagement.

When examining the association between age categories and preference for message type when viewing messages by micro-influencers, the preference for message type by preferred social media platform revealed no significant association between the variables. This suggests that when considering the current practices of participants across all age categories, neither the age category nor social media platform need to be specifically

considered when micro-influencers deliver messages on social media platforms, especially given that the informative message type is the most preferred on any social media platform (as revealed in the cross-tabulation) and among all age categories.

5.3. Social Media Message Strategy Preferences by Age Categories and Social Media Platforms (RQ3)

RQ3: How do the audiences' preferences for message strategies vary based on social media platforms and among diverse age audiences?

To address RQ3, a discrete choice experiment, a preference elicitation method, was used to determine if message strategy preferences, that is, preferences for message format and message type, vary by age categories and by social media platform preferences.

5.3.1. RQ3 Summary of Key Findings

Findings from the discrete choice experiment suggest that when determining the message type used in a health and wellbeing message, micro-influencers should consider audience age and social media platform to help ensure that the information needs of the target audience are met because age and social media platform preference moderated the relationship between message type and message strategy preference. Conversely, there appears to be less need for micro-influencers to consider age or social media platform when deciding on the message format to use when creating and sharing health and wellbeing messages because neither age nor social media platform preference moderated the relationship between message format and message strategy preference. Given that micro-influencers have a greater capacity to connect more intimately with audiences, this finding is novel, in that it extends our understanding of how micro-influencers can best align health and wellbeing message strategies with the information needs of age-diverse audiences and communicate more effectively.

5.3.2. Message Strategy Preferences by Age Categories

To test hypothesis 1_a, that is, audience age moderates the effect of message format on audiences' message strategy preferences, binary logistic regression was conducted with results revealing no significant interaction of age category on message format. Given that

age categories did not moderate audiences' preferences for message format, this suggests that audiences' preferences for message format does not vary among age-diverse audiences. As such, when deciding which message format to use when sharing health and wellbeing messages, micro-influencers do not need to specifically consider age categories.

When testing hypothesis 2_a, that is, audience age moderates the effect of message type on audiences' message strategy preferences, results showed that age categories did have a statistically significant interaction effect, moderating the relationship between message type and message strategy preferences. This ultimately suggests that preferences for message type do vary among diverse age categories.

While informative messages were the most preferred message type among the whole sample, discrete choice results show that the Baby Boomers/Post War age category significantly preferred informative messages more than the benchmark Gen Z age category. When compared with the cross-tabulation findings, this suggests that whilst there is no significant association between age categories and message type, there is a significant interaction effect. As such, when targeting messages to the Baby Boomers/Post War generation, micro-influencers and those utilising micro-influencers can feel more confident about incorporating an informative and educational lens into the message to meet the information needs of this age category. This is an especially important finding as there is limited research which has focused on older audiences and social media and message type preferences, and particularly given the older age category is becoming increasingly active in online spaces (Guner & Acarturk, 2020). This contributes to the micro-influencer and general influencer marketing literature by providing a critical insight into the message type preferences of the Baby Boomers/Post War generation. It also leverages the media richness theory which suggests that by aligning media, which in the case of the Baby Boomers/Post War generation is the use of informative elements in a message strategy, the information and communication needs of this age category are better met.

Whilst emotional content is considered best suited to rich forms of media and can result in a higher level of audience engagement (Shahbaznezhad et al., 2021), results from the current study showed that in comparison to the baseline Gen Z age category, Millennials and Gen X had a negative interaction effect on the message type preference of emotional or relatable

messages. The finding suggests that they are less likely to prefer micro-influencers to share emotional or relatable health and wellbeing messages. Conversely, Gen Z is the age category that most prefers micro-influencers to deliver health and wellbeing messages that resonate with them on an emotional level and this may extend to also include health and wellbeing messages that relate to social causes.

Interactive messages typically have a high level of media richness and therefore can generate a higher level of engagement from audiences (Shahbaznezhad et al., 2021). When examining the interactive message type, Gen X weakened the effect of the interactive message type on preference, suggesting that in comparison to the baseline message type of promotional and baseline age category of Gen Z, Gen X are less likely to prefer interactive health and wellbeing messages shared by micro-influencers. Therefore, if micro-influencers are targeting health and wellbeing messages to the Gen X age category specifically, they may have more success using alternative message types, such as promotional messages where audiences are rewarded or incentivised.

The interactions of age category on message types are complex. Applying a general overview of the findings reveals that in some instances age category does significantly moderate relationships between message type and preference for message type. The Baby Boomers/Post War age category prefers informative health and wellbeing messages, whilst Millennials and Gen X are less likely to prefer emotional or relatable health and wellbeing messages, with Gen X also less likely to prefer interactive messages.

On the other hand, Gen Z is the age category that most prefers micro-influencers to deliver health and wellbeing messages that resonate with them on an emotional level and less likely to prefer messages with an educative purpose. This finding partly aligns with existing literature which has also found that for messages regarding health and wellbeing, emotional appeals resonate strongly with audiences (Koinig, 2021; Noel et al., 2018; Wilson & Wolf, 2009; Xie et al., 2022). However, this study extends the knowledge in this field by focusing on the age categories that most prefer this message type. The results highlight that for micro-influencers who intend to share health and wellbeing messages, there are distinct message type preferences across age categories that are worth considering and addressing to maximise the extent to which the message type appeals to their audiences.

5.3.3. Message Strategy Preferences by Social Media Platform Preference

The categories of social media platforms considered in the current study included media sharing networks, which include platforms such as Instagram, YouTube, and TikTok; social networks, which include platforms such as Facebook and LinkedIn; and direct messaging platforms, which consist of social media platforms such as Facebook Messenger and WhatsApp. Social media platforms provide brands with a leverage for marketing purposes and for reaching and engaging with consumers (Appel et al., 2020; Gao et al., 2018; Li et al., 2020). The literature suggests that types of communication, namely text, pictures and video, can vary depending on the social media platform (Shane-Simpson et al., 2018). Further, audience engagement and reach can vary depending on the social media platform (Cao et al., 2021; Guidry et al., 2017; Khan, 2017; Wang et al., 2017), suggesting that it is important for brands to tailor messages to the type of social media platform (Vinerean, 2017).

This notion was further examined in this current study when addressing hypothesis 1_b, that is, social media platform preference moderates the effect of message format on audiences' message strategy preferences. Contrary to the literature, within the context of micro-influencer health and wellbeing messages, results revealed no significant interaction effect of social media platform preference on the relationship between message format and message preference. As such, the finding does not support the hypothesis and suggests that in relation to message format, message preferences do not vary based on audiences' preferred social media platform. This suggests that when delivering health and wellbeing messages, micro-influencers do not necessarily need to tailor the messaging format to the social media platform on which they are sharing the message. Rather, it may be more effective to consider the platform their target audience is most active on along with the message type used, which will be discussed in the following section.

In testing hypothesis 2_b, that is, social media platform preference moderates the relationship between message type and message strategy preferences, results revealed that in comparison to the baseline Media Sharing Networks, Direct Messaging Platforms had a significant negative interaction effect on the message type preference of emotional or relatable messages. This suggests that for micro-influencers who share health and wellbeing messages via a direct messaging platform, emotional or relatable message types are less likely to appeal to their audience. This is particularly interesting given that results also

revealed that generally, Millennials, Gen X, and Baby Boomers/Post War generations are less likely to prefer emotional or relatable messages when compared to Gen Z. Whilst emotional and relatable messages lend themselves to connecting with an audience through feelings and experiences (Tafesse & Wien, 2018), these types of messages may be better delivered via media sharing networks than direct messaging platforms and may resonate more with Gen Z than the remaining age categories.

5.4. Theoretical Contributions

This study has examined the social media practices of an age-diverse audience and their message format, message type, and social media platform preferences in relation to health and wellbeing messages delivered by micro-influencers.

Media richness theory states that communication effectiveness can be improved by aligning media to users' information needs (Lengel & Daft, 1984). There have been a small number of studies that have explored which message formats and social media platforms have a high level of media richness, for example, Leung et al. (2017) who focused on the hotel industry and Shahbaznezhad et al. (2021) who focused on the airline industry. This current study has applied media richness theory in the context of health and wellbeing messages shared by micro-influencers, therefore applying the media richness theory to a novel research context.

The focus of media richness in social media research has typically been on the message formats, message types, and social media platforms used to communicate with audiences. For example, in relation to social media platforms, Cao et al. (2021) found that brands should align the features and functionality of the platform with their marketing objectives to create an effective social media marketing strategy. Shahbaznezhad et al. (2021) also examined social media platforms and highlighted the importance of sharing the same message across a range of platforms. The current study has not only examined the preferred social media platforms across an age-diverse audience but has further examined how social media platform preference moderates the relationship between other elements of a message strategy, specifically message format and message type, and preferences of micro-influencer health and wellbeing message strategy. A key finding from the current study was that social media platform preference moderated the relationship between message type

and preferences of micro-influencer health and wellbeing message strategy. This highlights that depending on the message type, social media platforms can impact audiences' message strategy preferences. Media richness theory suggests that social media platforms are a key element of the 'media' used when micro-influencers share health and wellbeing messages.

Previous studies within the context of social media have looked at how media richness applies to engagement and communication (Cao et al., 2021; Moran et al., 2019; Shahbaznezhad et al., 2021), effectiveness of a message (Kusumasondjaja, 2018) and purchase intentions (Adelaar et al., 2003). This study revealed that there are some unique differences in the message strategy preferences of different age categories, reinforcing a key underpinning of the media richness theory whereby aligning media to users' information needs can increase message effectiveness (Daft & Lengel, 1983). Although the findings of the discrete choice experiment revealed social media platform (by preference) may not be as important a consideration for micro-influencers sharing health and wellbeing messages across all ages, the chi-square results highlighted that different age groups do have different social media platform preferences. While the Baby Boomer/Post War age category prefer social networks, Gen Z prefer media sharing networks. In relation to one of the four distinguishing factors of the media richness theory, the feedback capability of the medium (Cao et al., 2021), this contributes to theory by extending knowledge about age categories and the level of richness they prefer in regard to social media platforms. Specifically, older people prefer rich forms of media such as Facebook, and younger people prefer less rich forms of media such as Instagram.

Message format, another vital element of a message strategy, has been examined in various contexts. For example, Shahbaznezhad et al. (2021) and Moran et al. (2019) both found that message format can impact engagement behaviours in their studies which focused on the airline industry and the media and entertainment industry respectively. Leung et al. (2017) who focused on the hotel industry, found that message formats can have implications on the effectiveness of message strategies. However, in the current study, which focused on health and wellbeing messages shared by micro-influencers, message format did not require specific consideration within a message strategy across age-diverse audiences.

Whilst the literature suggests that a high level of media richness increases engagement and visibility (Moran et al., 2019), some studies have suggested that there are instances where low media richness is appropriate, for example, when communicating standard information (Daft & Lengel, 1986). This current study has revealed that video, which is considered a high media rich format (Moran et al., 2019; Shahbaznezhad et al. 2021), was the most preferred message format across all age categories when viewing health and wellbeing messages shared by micro-influencers. Conversely, text, which is generally considered a low media-rich format (Moran et al., 2019), was the least preferred message format across all ages. In the context of the current study, the results support the notion that media-rich messages are more likely to appeal to age-diverse audiences when viewing health and wellbeing messages shared by micro-influencers. Further, within the context of age-diverse audiences viewing health and wellbeing messages delivered by micro-influencers, the current study found that:

- Message format preferences do not differ based on age.
- Media sharing networks such as Instagram are preferred by Gen Z, Millennials, and Gen X age categories.
- Social networks such as Facebook are preferred by Baby Boomers/Post War.
- Informative was the most preferred message type across all age categories, with promotional the least preferred across all ages.
- Social media platform preference moderates the relationship between message type and preference for message type.
- Age moderates the relationship between message type and preference for message type.

The above insights highlight potentially important considerations when crafting a message to maximise communication effectiveness.

The seminal work of Daft and Lengel (1983, 1986) and Lengel and Daft (1984) proposed that different variations in media can impact the effectiveness of how information is processed by the receiver. More recent research also has focused on what may contribute to effective messaging. For example, Lodhia (2018) examined the use of newer media such as social media to deliver effective messaging that transforms practices, and Shahbaznezhad et al.

(2021) examined how the interaction of different elements of message strategy can impact the effectiveness of the message. Whilst the focus of the current study has been on the preferences of age-diverse audiences in relation to micro-influencer message strategies within the health and wellbeing context, and not specifically the construct of effectiveness, gaining an understanding of the preferences of age-diverse audiences can help micro-influencers to tailor their messaging more effectively.

Additional theoretical implications from the current study relate to the social media and the influencer marketing literatures. Influencer marketing has been recognised as one way in which social media can be used to disseminate health and wellbeing-related messages (Byrne et al., 2017; Lim et al., 2022). However, there is a dearth of research regarding which social media messaging strategies most appeal to age-diverse audiences when viewing health and wellbeing messages (Pagoto et al., 2019), particularly in the context of micro-influencer marketing. Findings from this study advance our understanding regarding social media practices of age-diverse audiences, including the social media practices of each age category and the time they are most active, types of devices used when accessing social media, the number of social media accounts and type of social media activities that age-diverse audiences engage in, and their reasons for using social media. Importantly, the findings contribute to our understanding of generation-specific social media practices, especially for those in the Baby Boomers/Post War generation – an age category for which there is limited research. However, there is still a need for further, larger studies to be conducted with the Baby Boomers/Post War age category, particularly given the policy priority of digital inclusion (Office for Ageing Well, 2019).

Age has been considered as a construct in several previous social media and influencer marketing studies. For example, Arora et al. (2018) investigated the platform preferences of Millennials, and Shane-Simpson et al. (2018) examined the social media platform preferences of 18–25-year-olds. This current study has extended the evidence-base regarding age and social media by explicitly examining social media practices and micro-influencer message strategy preferences with a sample aged 18 to 78 years. This study also contributes to the social media literature by drawing comparisons with multiple age categories and further considers these comparisons within the important area of health and wellbeing and with the current popular marketing strategy, micro-influencer marketing.

In the influencer marketing literature, it is known that influencer marketing relies heavily on communication and incorporates two key characteristics: impact and reach. With influencers playing a role in public health promotion (Looi et al., 2022), this study has contributed to the field by examining the delivery of health and wellbeing messages by micro-influencers. The findings have implications for micro-influencer marketing as it can inform how micro-influencers can maximise impact and reach. By understanding the message strategy preferences of age-diverse audiences when receiving health and wellbeing messaging, micro-influencers can effectively tailor their message. For example, in understanding that different age categories have varying social media practices and message strategy preferences this can be leveraged to achieve successful micro-influencer marketing outcomes.

Despite a smaller follower count in comparison to macro-influencers or celebrities, micro-influencers possess a substantial following and audience. Moreover, what sets them apart is their ability to establish deeper connections and interactions with their followers on a more personal and intimate level (Farivar et al., 2021; Olsen & Sandholmen, 2019). This study has highlighted that an understanding of preferences of an age-diverse audience in relation to micro-influencer health and wellbeing messages can further enhance a micro-influencer's capacity to connect with their audience in the way they most prefer and may be worth considering within a micro-influencer marketing strategy.

The perspectives provided by the age-diverse sample in the current study are critical in helping to further our understanding of the media (social media message strategy) which best aligns with the preferences and information needs of age-diverse audiences. Further, the current study has brought together in a novel way, media richness theory (Daft & Lengel, 1983, 1986; Lengel & Daft, 1984), social media, and influencer marketing concepts to advance knowledge about social media practices of age-diverse audiences and their preferences related to micro-influencer health and wellbeing message strategies.

5.5. Industry and Social Implications

Several industry and social implications arise from the findings of this current research. The findings highlight both direct and indirect implications for the three main stakeholder groups relevant to this study. These stakeholders include brands and those who utilise

micro-influencers for marketing purposes, micro-influencers themselves, and social media users, specifically, audiences who follow or would follow micro-influencers.

First, findings from the current study can inform the decision-making of:

- health and wellbeing brands
- those who utilise micro-influencers for health and wellbeing marketing
- those who have a campaign with broad age appeal or who want to target audiences of diverse ages.

Improved decision-making ensures that communication and message strategies better align with the information needs and preferences of age-diverse audiences. It also maximises connection with the audience and the reach and impact of messages. Examples include:

- Media sharing platforms should be used to deliver health and wellbeing messages to Gen Z, Millennials and Gen X, and social networks should be used if the aim is to connect with Baby Boomers/Post War.
- Media rich message formats, particularly video, should be used to communicate health and wellbeing messages across age-diverse audiences.
- Message type needs to be considered when creating health and wellbeing messages, to maximise the appeal of the message to each specific age category. The potential benefits of sharing informative health and wellbeing messages also need to be considered, given that this message type is preferred across age-diverse audiences. Additionally, avoid the use of emotional or relatable message types on direct messaging platforms across age-diverse audiences. Instead consider other media sharing networks or social networks for disseminating emotional or relatable messages. Also consider alternatives to emotional and relatable message types when sharing health and wellbeing messages with Millennials and Gen X.

Second, using the expanded insights into the social media practices of age-diverse audiences generated from this study, micro-influencers can apply the findings to inform how and when they can better connect, communicate and engage with their followers and further meet their marketing objectives. Specifically:

- Consider the timing of message delivery. For example, it is more likely to reach Baby Boomers/Post War in the morning, whereas Gen Z can be reached throughout the day as they indicated they constantly access social media.
- Consider social media platform reach and distribution. For example, Baby Boomers/Post War and Gen X had fewer than five accounts with different social media platforms, whilst Gen Z were more likely than expected to have in excess of 11 social accounts. Therefore, if targeting health and wellbeing messages to age-diverse audiences, a multi-platform social media approach may be warranted.

Third, a key social implication is that the findings from the current study provide insights that align with, and can be used by, micro-influencers and stakeholders associated with health and wellbeing to action the key digital inclusion objective of the South Australian Department for Health and Wellbeing's Office for Ageing Well (2019). Better understanding the practices, preferences and information needs of an age-diverse audience, and particularly of older age categories, can help micro-influencers to enact practices that support digital inclusion, and ensure that those who need to receive important health and wellbeing messages *are* receiving the message.

Finally, it is critical that health and wellbeing messages reach and resonate with age-diverse audiences when shared online, and in particular when shared on social media. The findings from the current study can help tailor health and wellbeing messages to align with the social media practices and information needs and preferences of age-diverse audiences. This will enable followers and audiences of micro-influencers to view messages in the format and type they most prefer, optimising their online experience when viewing health and wellbeing messages, and potentially maximising audiences' receptiveness to the message.

Table 37 below provides a summary of the findings of this study and key theoretical and practical implications.

Table 37: Findings and Implications

Findings	**Theoretical Contributions**	**Industry Implications**
How do social media practices, generally and in relation to micro-influencers, vary among age-diverse audiences?		

• Reason for using social media
  ○ *Connect, communicate, and stay in touch* with others was a primary reason to use social media across all age categories.
• Accessing social media
  ○ Gen Z are more likely to access social media throughout the day, whilst Baby Boomers/Post War and Gen X are more likely to access social media in the morning.
• Type of social media platform
  ○ Gen Z, Millennials, and Gen X are **most active** on media sharing networks (e.g., Instagram) whilst Baby Boomers/Post War are **most active** on social networks (e.g., Facebook).
• Social media practices related to micro-influencers
  ○ *Inspiration and ideas* was a key motivation for following micro-influencers across all age categories.
  ○ Gen Z is most likely to follow micro-influencers.
  ○ If Baby Boomers/Post War were not already following micro-influencers, they would not follow micro-influencers in the future.
	• Increased understanding regarding:
	  ○ Generation-specific social media practices, including insights into:
	  ▪ Baby Boomers/Post War generation for which there is limited research.
	  ▪ Age-diverse audiences given the study sample has representation across ages 18 to 78 years.
	  ▪ The relationship between social media practices of age-diverse audiences and micro-influencer marketing in health and wellbeing.
		• In line with existing **social media platform practices** of age-diverse audiences, the type of social media platform should be considered by micro-influencers when delivering health and wellbeing messages:
		  ○ Media sharing platforms for Gen Z, Millennials and Gen X.
		  ○ Social networks should be used if the aim is to connect with Baby Boomers/Post War.
		• When delivering health and wellbeing messaging across age-diverse audiences, micro-influencers should consider:
		  ○ Implementing a multi-platform approach given the number of social media accounts varied across age categories.
		  ○ The timing of when they share messages given the time-of-day social media is accessed varies across age categories:
		  ▪ Baby Boomers/Post War in the morning,
		  ▪ Gen Z can be reached throughout the day as they indicated they constantly access social media.

What social media platforms do audiences of health and wellbeing micro-influencers prefer?		
• Platform preferences of age-diverse audiences.	• Increased insights into:	• To align with **social media platform preferences** of age-diverse audiences when

○ Different age categories preferred different social media platforms: ▪ Baby Boomers/Post War **most preferred** social networks, such as Facebook, ▪ Gen Z, Millennials, and Gen X **most preferred** media sharing networks, such as Instagram.	○ Possible links between social media platform practices and social media platform preferences: ▪ **Social media platform practices** in a general context and **social media platform preferences** specific to micro-influencer health and wellbeing messaging are aligned when examined by age categories, therefore, social media platform practices may be considered a potential indicator of social media platform preferences of age-diverse audiences. • Feedback capability and social media platform preferences: ○ Media richness theory relates to immediacy of feedback (Lengel and Daft, 1984), and different social media platforms enable varying levels of feedback (Cao et al., 2021). ○ Given differences in social media platform preferences across age categories, age-diverse audiences may prefer differing levels of feedback capability when receiving health and wellbeing messages from micro-influencers.	receiving health and wellbeing messaging, micro-influencers should consider the feedback capability of the social media platform and in line with preferences use: ○ Social networks to reach Baby Boomers/Post War, ○ Media sharing networks for Gen Z, Millennials, and Gen X.
What social media message formats do audiences of health and wellbeing micro-influencers prefer?		
• Social media message format preferences of age-diverse audiences. ○ Video was the most preferred message format across all age categories, ○ Text was the least preferred message format across all age categories.	• Increased insights into media richness theory, specifically related to message format, within the context of micro-influencer marketing and health and wellbeing messaging: ○ Previous studies suggest the richness of the format can determine the level of engagement (Moran et al., 2019).	• When delivering health and wellbeing messaging across age-diverse audiences, micro-influencers should consider: ○ **Incorporating video**, a media rich format, as part of their message strategy to align with preferences of an age-diverse

	○ Given that a media rich format was preferred across all age categories whilst message formats with a low level of media richness were least preferred, micro influencer marketing approaches may benefit from drawing on media richness theory (Daft & Lengel, 1983) when delivering health and wellbeing messages. • Social media message format preferences ○ Whilst previous studies have examined the relationship between *engagement* and message format, the current study has focused on the *preferences* of message format across age-diverse audiences when receiving health and wellbeing messages from micro-influencers, which may be a precursor to gaining further understanding related to engagement.	audience and to help maximise impact and reach.
What social media message types do audiences of health and wellbeing micro-influencers prefer?		
• Social media message type preferences of age-diverse audiences. ○ Informative messages were most preferred across all age categories, ○ Promotional was the least preferred message type across all ages.	• Previous research has highlighted the importance of aligning media to users' information needs (Daft and Lengel, 1986), and shown that the rational/informative message type can significantly predict engagement (Shahbaznezhad et al., 2021), therefore, • Influencer marketing may benefit from incorporating users' preferences for informative message type to help increase communication effectiveness and engagement.	• When delivering health and wellbeing messaging across age-diverse audiences, micro-influencers should consider: ○ **Using informative** message types and limit promotional messages.

How do the audiences' preferences for message strategies vary based on social media platforms and among age-diverse audiences?		

• Audience preferences for message strategies
  ○ Age and social media platform moderate the relationship between message type and preferences of micro-influencer health and wellbeing message strategy.
  ○ Age and social media platform do not moderate the relationship between message format and preferences of micro-influencer health and wellbeing message strategy.
	• In media richness theory, 'media' refers to the media used to communicate information, and variations in communication media can impact the way information is processed by the receiver (Daft and Lengel, 1986).
	  ○ The current study contributes insights into relationships between key elements of *media*, namely message format, type and social media platform within the context of influencer marketing and age-diverse audiences.
	  ○ Preferences for message type, and social media platform may also impact the way information is processed by the receiver, with the interaction of age, and social media platform predicting preferences of message types.
		• When delivering health and wellbeing messaging across age-diverse audiences, micro-influencers should:
		  ○ Consider **audience age** and **social media platform** when determining the **message type,** however,
		  ▪ Audience age and social media platform are not key considerations when determining message format.
		  ○ **Avoid** the use of **emotional or relatable message types** on **direct messaging platforms**.

5.6. Strengths and Limitations of the Study

The study is not without limitations. As a cross-sectional online survey, it is important to note that this type of survey design provides data that represents a snapshot in time. In this study, this relates to the collection of data about participants' social media practices and message strategy preferences at one specific point in time. Given that the study did not require measures to be considered over time, the online cross-sectional survey design was considered an appropriate and efficient method of data collection.

Whilst the discrete choice experiment closely represented real-life choices, the presentation of the stimuli, which in this survey was the message strategies in the choice sets, can be considered unnatural in comparison to seeing a message strategy presented through a post on social media. Also, responses measured the most preferred option relative to the remaining options, without considering a participant's preferences relative to the non-chosen options (Louivere et al., 2000); that is, participants did not have a 'no choice' option for each choice set in the discrete choice experiment.

In regard to preferences of message strategies, a limitation of this study is that it did not take into account the nuances of micro-influencer messages such as, when micro-influencers share messages that are sponsored by a private company or if it is a public health message. Participants may have different preferences for message strategies when the sender behind the message is not just the micro-influencer who may only be the avenue for sharing.

Whilst acknowledging that social media studies tend to rely on self-report survey designs (Kuru & Pasek, 2016), given that the current study employed purposive and convenience sampling strategies, it is important to note the potential for various response biases. It is possible that self-selection bias exists because individuals with an interest in the topic may have been more receptive and inclined to complete the online survey. As such, there is a possibility that the characteristics of the participants who participated in the current study may differ in reality from those who chose not to participate in the study. In future, studies which employ probability sampling strategies with a larger number of participants across age categories may be helpful in further expanding our understanding of message strategy

preferences of an age-diverse audience when receiving health and wellbeing messages from micro-influencers.

To address the potential for acquiescence bias, that is agreement bias, whereby survey participants are more likely to answer in the affirmative (Kuru & Pasek, 2016), or in a way in which they think aligns with societal expectations (Dursun et al., 2019), careful consideration was given to the wording of survey items and to the response options provided. Importantly, with 'yes/no' types of questions, an 'unsure' option also was included to reduce the potential acquiescence bias. For example, the response options available for '*Would you consider following a micro-influencer in the future?*' included 'Yes', 'No', and 'Unsure'.

Although there are limitations, there are also many strengths of this study. Worth noting is that, whilst there was an unequal distribution of numbers across age categories (for example, a lot more Gen Z than Baby Boomers/Post War), representation across all age categories was achieved. Further, acknowledging the limitations of convenience sampling, both online and offline recruitment strategies were employed. This enabled the researcher to maximise visibility and reach of the study. The survey was shared through numerous face-to-face and online avenues, including social media groups, micro-influencers, the researcher's networks, and local community groups via QR codes. Additionally, whilst there was a high percentage of female respondents, the gender distribution reflects the gender distribution of followers in popular categories of the influencer market (Lee et al., 2022).

To the researcher's knowledge, this is the first study to apply discrete choice methods to examine followers', or would-be followers', preference for message strategy when viewing health and wellbeing messages from micro-influencers. A particular strength is the systematic approach employed in developing the discrete choice experiment which drew heavily on the literature to inform the attributes and levels used.

Additionally, prior to publishing the online survey and actively recruiting participants, rigorous trialling and testing took place to address any errors or issues related to the survey design, accessibility and functionality, and readability. This helped ensure the successful dissemination and completion of the survey.

5.7. Directions for Future Research

This study highlights the need for further research on age-diverse audiences and their practices on social media, particularly given the increasing number of older people who are active online, and to ensure the evolution of digital and social media is informed by age-diverse audiences. As highlighted above, studies which employ probability sampling with greater representation within each age category will also be critical in extending our understanding in this field.

Employing the discrete choice experiment beyond micro-influencers to incorporate other categories of influencers such as macro-influencers and/or mega-influencers could provide further useful insights into the topic. Additionally, employing a discrete choice experiment that focuses on one specific type of health and wellbeing topic, such as public health, fitness, or nutrition, could enable further tailoring of related messages to maximise reach and impact. This of course could be extended beyond the health and wellbeing context to other categories in the influencer market, such as fashion, gaming, and beauty.

Methodologically, there is scope to replicate the current study with the addition of a 'no choice' option within the discrete choice experiment. This could serve to both validate the findings of the current study and to address any potential bias that may arise by not providing a 'no choice' option.

When drilling down to the next level of message type, that is, beyond the rational, transactional, interactional, and transformational, and given that relaxation and entertainment are identified as key reasons for following micro-influencers, future research could explore these additional constructs. Future studies could consider how relaxation and entertainment can be incorporated in micro-influencer health and wellbeing messages to age-diverse audiences to ensure that their information needs are met (Lengel & Daft, 1984).

Further, whilst the current study provides data that captures a snapshot in time, employing a longitudinal survey study could help to map changes in preferences over time. Following the generation as they age could provide much-needed information that would help ensure that message strategies employed by micro-influencers when sharing health and wellbeing messages remain relevant and continue to align with the information needs of age-diverse audiences (Lengel & Daft, 1984).

Studies that consider alternative moderating variables beyond age and social media platform preference are warranted, as there is a possibility that variables such as high use or engagement on a social media platform may impact the message format and type preferences. Further exploring any potential relationship between message format and message type may contribute to our understanding of message strategy preferences. For example, does message format predict or moderate the preference for message type?

The result that the Baby Boomers/Post War generation was unlikely to follow a micro-influencer in the future was surprising and warrants further investigation because this generation reported using social media to find and connect with like-minded communities and interest groups, which is a potential advantage of engaging with micro-influencers. A consideration for further research is to explore the extent to which those in the Baby Boomers/Post War age category are familiar with the term/concept of micro-influencer and/or the nature of any preconceptions about influencer marketing.

Lastly, future research could explore the topic in relation to the generational cohort theory which can further explain attitudes and opinions of micro-influencer health and wellbeing message strategies specific to age-diverse audiences (Thach et al., 2021).

5.8. Conclusion

This current study employed a cross-sectional survey design and discrete choice experiment to investigate the preferences of an age-diverse audience in relation to micro-influencer message strategies in health and wellbeing. The results revealed differences across age categories in relation to their social media practices, their social media platform preferences and their message type preferences. These findings have important implications for both theory and practice. The results have contributed insights into media richness theory within the context of micro-influencer marketing and health and wellbeing messages for age-diverse audiences. In particular, the effectiveness of health and wellbeing communication can be improved by aligning message strategies to the message type preferences of age-diverse audiences and to their preferred social media platform. Further, media-rich health and wellbeing messages are more likely to appeal to age-diverse audiences when shared by micro-influencers. From a practical industry perspective, the findings from this study provide micro-influencers, and those who utilise micro-influencer marketing, with current

insights into the social media practices and message strategy preferences of an age-diverse audience. Therefore, the current study will enable stakeholders to draw on the research findings to inform effective message strategies with a view to maximise the reach and impact of their health and wellbeing messages across age-diverse audiences.

The current study has highlighted several key areas for future research, to ensure that the field continues to build a strong evidence base on influencer marketing. This current research has contributed to the field of health and wellbeing micro-influencer marketing by drawing on media richness theory, generating results that can support micro-influencers to more intimately and effectively connect with audiences across all ages. It also produced findings that can be used to ensure that the information needs of age-diverse audiences are met, particularly when viewing messages related to health and wellbeing.

References

Addelman, S. (1962). Symmetrical and asymmetrical fractional factorial plans. *Technometrics, 4*(1), 47-58.

Adelaar, T., Chang, S., Lancendorfer, K. M., Lee, B., & Morimoto, M. (2003). Effects of media formats on emotions and impulse buying intent. *Journal of Information Technology, 18*(4), 247-266.

Adeola, O., Hinson, R. E., & Evans, O. (2020). Social media in marketing communications: A synthesis of successful strategies for the digital generation. In *Digital Transformation in Business and Society* (pp. 61-81). Springer.

Agostino, D., Arnaboldi, M., & Calissano, A. (2019). How to quantify social media influencers: An empirical application at the Teatro alla Scala.

Agresti, A., & Coull, B. A. (2002). The analysis of contingency tables under inequality constraints. *Journal of Statistical Planning and Inference, 107*(1-2), 45-73.

Aichner, T., Grünfelder, M., Maurer, O., & Jegeni, D. (2020). Twenty-Five Years of Social Media: A Review of Social Media Applications and Definitions from 1994 to 2019. *Cyberpsychology, Behavior, and Social Networking*.

Alampi, A. (2019). The future is micro: How to build an effective micro-influencer programme. *Journal of Digital & Social Media Marketing, 7*(3), 203-208.

Alassani, R., & Göretz, J. (2019). Product placements by micro and macro influencers on Instagram. In G. Meiselwitz (Eds.), *International conference on human-computer interaction* (pp. 251-267). Springer.

An, M. (2017). *Content Trends: Preferences Emerge Along Generational Fault Lines*. HubSpot. https://blog.hubspot.com/marketing/content-trends-preferences

Antwi, S. K., & Hamza, K. (2015). Qualitative and quantitative research paradigms in business research: A philosophical reflection. *European Journal of Business and Management, 7*(3), 217-225.

Appel, G., Grewal, L., Hadi, R., & Stephen, A. T. (2020). The future of social media in marketing. *Journal of the Academy of Marketing Science, 48*(1), 79-95.

Arensberg, M. B. (2018). Population aging: opportunity for business expansion, an invitational paper presented at the Asia-pacific economic cooperation (APEC) international workshop on Adaptation to population aging issues, july 17, 2017, Ha Noi, Viet Nam. *Journal of Health, Population and nutrition, 37*(1), 7.

Arora, T., Agarwal, B., & Kumar, A. (2018). A study of millennials's preferences for social media advertising in Delhi NCR. *Indian Journal of Marketing, 48*(10), 34-51.

Australian Bureau of Statistics. (2022). *Snapshot of Australia: 2021*. https://www.abs.gov.au/statistics/people/people-and-communities/snapshot-australia/latest-release#data-download

Australian Communications and Media Authority. (2020). *Misinformation and news quality on digital platforms in Australia: A position paper to guide code development*.

Auxier, B., & Anderson, M. (2021). Social Media Use in 2021. *Pew Research Center, 1*, 1-4. https://www.pewresearch.org/internet/2021/04/07/social-media-use-in-2021/

Barker, V. (2012). A generational comparison of social networking site use: The influence of age and social identity. *The International Journal of Aging and Human Development, 74*(2), 163-187.

Baškarada, S., & Koronios, A. (2018). A philosophical discussion of qualitative, quantitative, and mixed methods research in social science. *Qualitative Research Journal*.

Bech, M., & Gyrd-Hansen, D. (2005). Effects coding in discrete choice experiments. *Health economics, 14*(10), 1079-1083.

Bentley, K., Chu, C., Nistor, C., Pehlivan, E., & Yalcin, T. (2021). Social media engagement for global influencers. *Journal of Global Marketing, 34*(3), 205-219.

Beresford Research. (2022). *Age Range by Generation*. Beresford Research. https://www.beresfordresearch.com/age-range-by-generation/

Bethlehem, J. (1999). Cross-sectional research. *Research methodology in the social, behavioural and life sciences, 110*, 142.

Bezuidenhout, N. (2021). Capitalising on social media marketing to raise confidence in covid-19 public health information and vaccines. *Medical Writing, 30*, 12-15.

Bliemer, M. C., & Rose, J. M. (2014). Designing and Conducting Stated Choice Experiments. In S. Hess & A. Daly (Eds.), *Handbook of Choice Modelling* (2nd ed.). Edward Elgar Publishing.

Blystone, D. (2020). The Story of Instagram: The Rise of the #1 Photo-Sharing Application. *Investopedia* https://www.investopedia.com/articles/investing/102615/story-instagram-rise-1-photo0sharing-app.asp

Boerman, S. C. (2020). The effects of the standardized Instagram disclosure for micro-and meso-influencers. *Computers in Human Behavior, 103*, 199-207.

Bolton, R. N., Parasuraman, A., Hoefnagels, A., Migchels, N., Kabadayi, S., Gruber, T., Loureiro, Y. K., & Solnet, D. (2013). Understanding Generation Y and their use of social media: a review and research agenda. *Journal of service management*.

Britt, R. K., Hayes, J. L., Britt, B. C., & Park, H. (2020). Too Big to Sell? A computational analysis of network and content characteristics among mega and micro beauty and fashion social media influencers. *Journal of Interactive Advertising 20*(2), 111-118.

Brown, T. C., & Peterson, G. L. (2009). *An Enquiry Into the Method of Paired Comparison: Reliability, Scaling, and Thurstone's Law of Comparative Judgment* (Gen Tech. Rep. RMRS-GTR-216WWW. Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station. 98 p.

Bruhn, M., Schoenmueller, V., & Schäfer, D. B. (2012). Are social media replacing traditional media in terms of brand equity creation? *Management Research Review, 35*(9), 770-790. https://doi.org/10.1108/01409171211255948

Brunelle, E. (2009). Introducing media richness into an integrated model of consumers' intentions to use online stores in their purchase process. *Journal of Internet Commerce, 8*(3-4), 222-245.

Bunch, D., Louviere, J., & Anderson, D. (1996). A comparison of experimental design strategies for choice-based conjoint analysis with generic-attribute multinomial logit models. *University of California, Davis, Graduate School of Management Working Paper*, 11-96.

Byrne, E., Kearney, J., & MacEvilly, C. (2017). The Role of Influencer Marketing and Social Influencers in Public Health. *Proc. Nutr. Soc, 76*(OCE3). https://doi.org/10.1017/S0029665117001768

Campbell, C., & Farrell, J. R. (2020). More than meets the eye: The functional components underlying influencer marketing. *Business Horizons, 63*(4), 469-479.

Campbell, S. (2022, November 6, 2022). What Is The Best Social Media Platform For Influencer Marketing In 2022? *The Small Business Blog*.

https://thesmallbusinessblog.net/best-social-media-platform-for-influencer-marketing/
Cao, D., Meadows, M., Wong, D., & Xia, S. (2021). Understanding consumers' social media engagement behaviour: An examination of the moderation effect of social media context. *Journal of Business Research, 122*, 835-846.
Carlson, J. R., & Zmud, R. W. (1999). Channel expansion theory and the experiential nature of media richness perceptions. *Academy of Management Journal, 42*(2), 153-170.
Carson, R. T., & Louviere, J. J. (2011). A common nomenclature for stated preference elicitation approaches. *Environmental and Resource Economics, 49*(4), 539-559.
Carter, D. (2016). Hustle and brand: The sociotechnical shaping of influence. *Social Media+ Society, 2*(3), 1-12.
Casaló, L. V., Flavián, C., & Ibáñez-Sánchez, S. (2018). Influencers on Instagram: Antecedents and consequences of opinion leadership. *Journal of Business Research*, *117*, 510-519.
Cavana, R., Delahaye, B., & Sekeran, U. (2001). *Applied business research: Qualitative and quantitative methods*. John Wiley & Sons.
Chae, M.-J. (2020). The effects of message tone and formats of CSR messages on engagement in social media. *The Journal of Asian Finance, Economics, and Business, 7*(10), 501-511.
Chapple, C., & Cownie, F. (2017). An investigation into viewers' trust in and response towards disclosed paid-for-endorsements by YouTube lifestyle vloggers. *Journal of Promotional Communications, 5*(2).
Chen, Q., Min, C., Zhang, W., Wang, G., Ma, X., & Evans, R. (2020). Unpacking the black box: How to promote citizen engagement through government social media during the COVID-19 crisis. *Computers in Human Behavior, 110*, 106380.
Chetioui, Y., Butt, I., Fathani, A., & Lebdaoui, H. (2022). Organic food and Instagram health and wellbeing influencers: an emerging country's perspective with gender as a moderator. *British Food Journal*(ahead-of-print).
Cheung, M. L., Pires, G., & Rosenberger, P. J. (2020). The influence of perceived social media marketing elements on consumer–brand engagement and brand knowledge. *Asia Pacific Journal of Marketing and Logistics*, *32*(3), 695-720.
Chopra, A., Avhad, V., Jaju, & Sonali. (2020). Influencer Marketing: An Exploratory Study to Identify Antecedents of Consumer Behavior of Millennial. *Business Perspectives and Research*, *9*(1), 77-91.
Cochran, W. G. (1954). Some methods for strengthening the common χ 2 tests. *Biometrics, 10*(4), 417-451.
Coco, S. L., & Eckert, S. (2020). #sponsored: Consumer insights on social media influencer marketing. *Public Relations Inquiry*, *9*(2), 177-194.
Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd, Ed.). Routledge.
Coulter, K. S., & Roggeveen, A. (2012). "Like it or not". *Management research review., 35*(9), 878-899. https://doi.org/10.1108/01409171211256587
Daft, R. L., & Lengel, R. H. (1983). *Information richness. A new approach to managerial behavior and organization design*.
Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science, 32*(5), 554-571.
De Choudhury, M., Morris, M. R., & White, R. W. (2014). Seeking and sharing health information online: comparing search engines and social media [Paper

presentation]. SIGCHI conference on human factors in computing systems, Toronto, ON, Canada.
De Veirman, M., & Hudders, L. (2020). Disclosing sponsored Instagram posts: the role of material connection with the brand and message-sidedness when disclosing covert advertising. *International Journal of Advertising, 39*(1), 94-130.
De Veirman, M., Cauberghe, V., & Hudders, L. (2017). Marketing through Instagram influencers: the impact of number of followers and product divergence on brand attitude. *International Journal of Advertising, 36*(5), 798-828.
Dixon, S. (2022). *Distribution of Instagram users worldwide as of April 2022, by age and gender*. https://www.statista.com/statistics/248769/age-distribution-of-worldwide-instagram-users/
Dumbrell, D., & Steele, R. (2014). Social media technologies for achieving knowledge management amongst older adult communities. *Procedia-Social and Behavioral Sciences, 147*, 229-236.
Dursun, İ., Kabadayı, E. T., & Durmaz, A. (2019). When to consider social desirability bias (SDB) in consumer behavior studies? A Review on SDB-vulnerable concepts. *Business & Management Practices*, 233.
Dwivedi, A., Johnson, L. W., & McDonald, R. E. (2015). Celebrity endorsement, self-brand connection and consumer-based brand equity. *Journal of Product & Brand Management, 24*(5), 449-461.
Eastman, J. K., Iyer, R., Eastman, K. L., Gordon-Wilson, S., & Modi, P. (2021). Reaching the price conscious consumer: The impact of personality, generational cohort and social media use. *Journal of Consumer Behaviour, 20*(4), 898-912.
Ebrahim, R. S. (2020). The role of trust in understanding the impact of social media marketing on brand equity and brand loyalty. *Journal of Relationship Marketing, 19*(4), 287-308.
Enke, N., & Borchers, N. S. (2019). Social media influencers in strategic communication: A conceptual framework for strategic social media influencer communication. *International Journal of Strategic Communication, 13*(4), 261-277.
Erdogan, B. Z. (1999). Celebrity endorsement: A literature review. *Journal of Marketing Management, 15*(4), 291-314.
Escobar-Viera, C. G., Shensa, A., Bowman, N. D., Sidani, J. E., Knight, J., James, A. E., & Primack, B. A. (2018). Passive and active social media use and depressive symptoms among United States adults. *Cyberpsychology, Behavior, and Social Networking, 21*(7), 437-443.
Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics, 5*(1), 1-4.
Evans, N. J., Phua, J., Lim, J., & Jun, H. (2017). Disclosing Instagram influencer advertising: The effects of disclosure language on advertising recognition, attitudes, and behavioral intent. *Journal of Interactive Advertising, 17*(2), 138-149.
Farivar, S., Wang, F., & Yuan, Y. (2021). Opinion leadership vs. para-social relationship: Key factors in influencer marketing. *Journal of Retailing and Consumer Services, 59*, 102371.
Finan, L. J., Lipperman-Kreda, S., Grube, J. W., Balassone, A., & Kaner, E. (2020). Alcohol marketing and adolescent and young adult alcohol use behaviors: A systematic review of cross-sectional studies. *Journal of Studies on Alcohol and Drugs, Supplement,* (19), 42-56.

Fink, M., Koller, M., Gartner, J., Floh, A., & Harms, R. (2020). Effective entrepreneurial marketing on Facebook–A longitudinal study. *Journal of Business Research, 113*, 149-157.

Fisher, B. (2020). *UK Digital Trends by Generation 2020: Digital Habits Before, During and After the Pandemic*. https://www.emarketer.com/content/uk-digital-trends-by-generation-2020

Foreman, C. (2017, June 20, 2017). 10 Types of Social Media and How Each Can Benefit Your Business. https://blog.hootsuite.com/types-of-social-media/

Fulmer, T., Patel, P., Levy, N., Mate, K., Berman, A., Pelton, L., Beard, J., Kalache, A., & Auerbach, J. (2020). Moving Toward a Global Age-Friendly Ecosystem. *Journal of the American Geriatrics Society, 68*(9), 1936-1940.

Gao, H., Tate, M., Zhang, H., Chen, S., & Liang, B. (2018). Social media ties strategy in international branding: An application of resource-based theory. *Journal of International Marketing, 26*(3), 45-69.

Geiser, F. (2017). *Social media as a communication channel–Is it possible to build a digital brand and generate revenue streams simultaneously by applying influencer marketing?*

George, M. A., Anitsal, I., & Anitsal, M. M. (2021). Influencer Marketing and the Everchanging Domain of Social Media Marketing. *Global Journal of Business Disciplines, 5*(1), 48.

Gil-Clavel, B. S., Zagheni, E., & Bordone, V. (2020). Close social networks among older adults: the online and offline perspectives. *Population Research and Policy Review, 41(3),* 1111-1135.

Godey, B., Manthiou, A., Pederzoli, D., Rokka, J., Aiello, G., Donvito, R., & Singh, R. (2016). Social media marketing efforts of luxury brands: Influence on brand equity and consumer behavior. *Journal of Business Research, 69*(12), 5833-5841.

Gómez, A. R. (2019). Digital Fame and Fortune in the age of Social Media: A Classification of social media influencers. *aDResearch: Revista Internacional de Investigación en Comunicación* (19), 8-29.

Greenfield, E. A., Oberlink, M., Scharlach, A. E., Neal, M. B., & Stafford, P. B. (2015). Age-friendly community initiatives: Conceptual issues and key questions. *The Gerontologist, 55*(2), 191-198.

Guidry, J. P., Austin, L. L., Carlyle, K. E., Freberg, K., Cacciatore, M., Meganck, S., Jin, Y., & Messner, M. (2018). Welcome or not: Comparing #refugee posts on Instagram and Pinterest. *American Behavioral Scientist, 62*(4), 512-531.

Guidry, J. P., Jin, Y., Orr, C. A., Messner, M., & Meganck, S. (2017). Ebola on Instagram and Twitter: How health organizations address the health crisis in their social media engagement. *Public relations review, 43*(3), 477-486.

Guner, H., & Acarturk, C. (2020). The use and acceptance of ICT by senior citizens: a comparison of technology acceptance model (TAM) for elderly and young adults. *Universal Access in the Information Society, 19*(2), 311-330.

Gupta, S., Dash, S. B., & Mahajan, R. (2021). The role of social influencers for effective public health communication. *Online Information Review*.

Guzmán, J. N. C., Ordóñez de Pablos, P., & Idemudia, E. C. (2020). Decision Making and Behavior. *Handbook of Research on IT Applications for Strategic Competitive Advantage and Decision Making*, 390-404. https://doi.org/10.4018/978-1-7998-3351-2.ch020

Hall, J. (2008). Encyclopedia of Survey Research Methods. In. Sage Publications, Inc. https://doi.org/10.4135/9781412963947

Hamilton, M., Kaltcheva, V. D., & Rohm, A. J. (2016). Social media and value creation: the role of interaction satisfaction and interaction immersion. *Journal of Interactive Marketing, 36*, 121-133.

Hatton, G. (2018). Micro Influencers vs Macro Influencers. *Social Media Today*. https://www.socialmediatoday.com/news/micro-influencers-vs-macro-influencers/516896/

Heinrichs, J. H., Lim, J. S., & Lim, K. S. (2011). Influence of social networking site and user access method on social media evaluation. *Journal of Consumer Behaviour, 10*(6), 347-355.

Heldman, A. B., Schindelar, J., & Weaver, J. B. (2013). Social media engagement and public health communication: implications for public health organizations being truly "social". *Public Health Reviews, 35*(1), 13.

Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). *Applied Choice Analysis: A Primer*. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511610356

Hu, B., Isakoff, S. J., Glieberman, E., O'Rourke, E., Spring, L., Moy, B., Bardia, A., Said, M., & Peppercorn, J. M. (2022). Baseline preferences for digital information engagement in patients with breast cancer by age and status of diagnosis.

Hu, W., Sun, S., Penn, J., & Qing, P. (2022). Dummy and effects coding variables in discrete choice analysis. *American Journal of Agricultural Economics*.

Huang, Y., & Wang, W. (2020). When a story contradicts: correcting health misinformation on social media through different message formats and mechanisms. *Information, Communication & Society*, 1-18.

Huber, J., & Zwerina, K. (1996). The importance of utility balance in efficient choice designs. *Journal of Marketing Research, 33*(3), 307-317.

Hudders, L., De Jans, S., & De Veirman, M. (2020). The commercialization of social media stars: a literature review and conceptual framework on the strategic use of social media influencers. *International Journal of Advertising*, 1-49.

IBM SPSS Statistics. (2022). SPSS Statistics (Version 28.0.1.1.) [Computer software]. https://www.ibm.com/au-en/spss

Jaakonmäki, R., Müller, O., & Vom Brocke, J. (2017). The impact of content, context, and creator on user engagement in social media marketing. *Proceedings of the 50th Hawaii international conference on system sciences*.

Jiménez-Castillo, D., & Sánchez-Fernández, R. (2019). The role of digital influencers in brand recommendation: Examining their impact on engagement, expected value and purchase intention. *International journal of information management, 49*, 366-376. https://doi.org/10.1016/j.ijinfomgt.2019.07.009

Johnson, F. R., Lancsar, E., Marshall, D., Kilambi, V., Mühlbacher, A., Regier, D. A., Bresnahan, B. W., Kanninen, B., & Bridges, J. F. (2013). Constructing experimental designs for discrete-choice experiments: report of the ISPOR conjoint analysis experimental design good research practices task force. *Value in Health, 16*(1), 3-13.

Kankam, P. K. (2019). The use of paradigms in information research. *Library & Information Science Research, 41*(2), 85-92.

Kannan, P., & Li, H. (2017). Digital marketing: A framework, review and research agenda. *International Journal of Research in Marketing, 34*(1), 22-45.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons, 53*(1), 59-68.
Kemp, S. (2020, 21 July 2020). Digital 2020 - July Global Statshot Report. https://wearesocial.com/blog/2020/07/more-than-half-of-the-people-on-earth-now-use-social-media
Kemp, S. (2021). *Digital 2021: The Latest Insights into the 'State of Digital'* (Digital 2021, Issue. W. A. Social. https://wearesocial.com/blog/2021/01/digital-2021-the-latest-insights-into-the-state-of-digital
Kemp, S. (2021a). *Digital 2021: Australia* (Digital 2021, Issue. W. A. Social. https://datareportal.com/reports/digital-2021-australia
Kemp, S. (2021b). *Digital 2021: The Latest Insights into the 'State of Digital'* (Digital 2021, Issue. W. A. Social. https://wearesocial.com/blog/2021/01/digital-2021-the-latest-insights-into-the-state-of-digital
Kemp, S. E., Ng, M., Hollowood, T., & Hort, J. (2018). Introduction to descriptive analysis. *Descriptive analysis in sensory evaluation, 1*.
Khan, M. L. (2017). Social media engagement: What motivates user participation and consumption on YouTube? *Computers in Human Behavior, 66*, 236-247.
Ki, C. W. C., & Kim, Y. K. (2019). The mechanism by which social media influencers persuade consumers: The role of consumers' desire to mimic. *Psychology & marketing, 36*(10), 905-922.
Ki, C.-W., Cuevas, L. M., Chong, S. M., & Lim, H. (2020). Influencer marketing: Social media influencers as human brands attaching to followers and yielding positive marketing results by fulfilling needs. *Journal of Retailing and Consumer Services, 55*, 102133.
Kim, D. Y., & Kim, H.-Y. (2022). Social media influencers as human brands: an interactive marketing perspective. *Journal of Research in Interactive Marketing*.
Kim, M. J., Lee, C.-K., & Contractor, N. S. (2019). Seniors' usage of mobile social network sites: Applying theories of innovation diffusion and uses and gratifications. *Computers in Human Behavior, 90*, 60-73.
Kim, M., Song, D., & Jang, A. (2021). Consumer response toward native advertising on social media: the roles of source type and content type. *Internet research*, 1066-2243.
Kingsnorth, S. (2019). *Digital marketing strategy: an integrated approach to online marketing*. Kogan Page Publishers.
Koinig, I. (2021). On the influence of message/audience specifics and message appeal type on message empowerment: the austrian case of covid-19 health risk messages. *Health Communication*, 1-12.
Kolo, C., & Haumer, F. (2018). Social media celebrities as influencers in brand communication: An empirical study on influencer content, its advertising relevance and audience expectations. *Journal of Digital & Social Media Marketing, 6*(3), 273-282.
Kostygina, G., Tran, H., Binns, S., Szczypka, G., Emery, S., Vallone, D., & Hair, E. (2020). Boosting Health Campaign Reach and Engagement Through Use of Social Media Influencers and Memes. *Social Media + Society, 6*(2), 1-12. https://doi.org/10.1177/2056305120912475
Kotnowski, K., Fong, G. T., Gallopel-Morvan, K., Islam, T., & Hammond, D. (2015). The impact of cigarette packaging design among young females in Canada: findings from a discrete choice experiment. *Nicotine & Tobacco Research, 18*(5), 1348-1356.

Kuerbis, A., van Stolk-Cooke, K., & Muench, F. (2017). An exploratory study of mobile messaging preferences by age: Middle-aged and older adults compared to younger adults. *Journal of Rehabilitation and Assistive Technologies Engineering, 4*, 1-10.

Kuhfeld, W. (2009). Marketing Research Methods in SAS Experimental Design, Choice. *Conjoint and Graphical Techniques. Technical Report*.

Kuhfeld, W. F. (2010). Experimental Design: Efficiency, Coding, and Choice Designs. *SAS Technical Papers*.

Kuhfeld, W. F. (2010a). Discrete Choice. *SAS Technical Papers*.

Kuhfeld, W. F. (2010b). Experimental Design: Efficiency, Coding, and Choice Designs. *SAS Technical Papers*.

Kuhfeld, W. F., Tobias, R. D., & Garratt, M. (1994). Efficient experimental design with marketing research applications. *Journal of Marketing Research, 31*(4), 545-557.

Kuru, O., & Pasek, J. (2016). Improving social media measurement in surveys: Avoiding acquiescence bias in Facebook research. *Computers in Human Behavior, 57*, 82-92.

Kusumasondjaja, S. (2018). The roles of message appeals and orientation on social media brand communication effectiveness. *Asia Pacific Journal of Marketing and Logistics, 30*(4), 1135-1158.

Laerd Statistics. (n.d.). *Binomial Logistic Regression Analysis using Stata*. https://statistics.laerd.com/stata-tutorials/binomial-logistic-regression-using-stata.php

Latha, K., Meena, K., Pravitha, M., Dasgupta, M., & Chaturvedi, S. (2020). Effective use of social media platforms for promotion of mental health awareness. *Journal of Education and Health Promotion, 9*. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7325786/

Lavrakas, P. J. (2008). *Encyclopedia of Survey Research Methods*. Thousand Oaks: SAGE Publications.

Lazard, A. J. (2021). Social media message designs to educate adolescents about e-cigarettes. *Journal of Adolescent Health, 68*(1), 130-137.

Ledford, C. J. (2012). Changing channels: A theory-based guide to selecting traditional, new, and social media in strategic social marketing. *Social Marketing Quarterly, 18*(3), 175-186.

Lee, J. A., Sudarshan, S., Sussman, K. L., Bright, L. F., & Eastin, M. S. (2022). Why are consumers following social media influencers on Instagram? Exploration of consumers' motives for following influencers and the role of materialism. *International Journal of Advertising, 41*(1), 78-100.

Lee, R. K.-W., Hoang, T.-A., & Lim, E.-P. (2017). On analyzing user topic-specific platform preferences across multiple social media sites. *Proceedings of the 26th International Conference on World Wide Web*.

Lengel, R. H., & Daft, R. L. (1984). *An exploratory analysis of the relationship between media richness and managerial information processing*.

Leung, X. Y., Bai, B., & Erdem, M. (2017). Hotel social media marketing: a study on message strategy and its effectiveness. *Journal of Hospitality and Tourism Technology, 8*(2), 239-255.

Li, F., Larimo, J., & Leonidou, L. C. (2020). Social media marketing strategy: definition, conceptualization, taxonomy, validation, and future agenda. *Journal of the Academy of Marketing Science*, *49,* 51-70.

Lim, M. S., Molenaar, A., Brennan, L., Reid, M., & McCaffrey, T. (2022). Young Adults' Use of Different Social Media Platforms for Health Information: Insights From Web-Based Conversations. *Journal of medical Internet research, 24*(1), e23656.

Liu, X., Shin, H., & Burns, A. C. (2021). Examining the impact of luxury brand's social media marketing on customer engagement: Using big data analytics and natural language processing. *Journal of business research, 125*, 815-826. https://doi.org/10.1016/j.jbusres.2019.04.042

Lodhia, S. (2018). Is the medium the message?. *Meditari Accountancy Research, 26*(1), 2-12.

Looi, J., Kemp, D., & Song, Y. W. G. (2022). Instagram Influencers in Health Communication: Examining the Roles of Influencer Tier and Message Construal in COVID-19-Prevention Public Service Announcements. *Journal of Interactive Advertising*, 1-19.

Lou, C., & Yuan, S. (2019). Influencer marketing: how message value and credibility affect consumer trust of branded content on social media. *Journal of Interactive Advertising, 19*(1), 58-73.

Louviere, J. (2001). Choice Experiments: an Overview of Concepts and Issues. In Bennet, J. & Blamey, R. (Eds.) The Choice Modelling Approach to Environmental Valuation. In. Edward Elgar Publishing Limited.

Louviere, J. J., Flynn, T. N., & Carson, R. T. (2010). Discrete choice experiments are not conjoint analysis. *Journal of Choice Modelling, 3*(3), 57-72.

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated Choice Methods: Analysis and Applications*. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511753831

Luca, M. (2015). User-Generated Content and Social Media. *Handbook of Macroeconomics., 1*, 563-592. https://doi.org/10.1016/b978-0-444-63685-0.00012-7

Lyson, H. C., Le, G. M., Zhang, J., Rivadeneira, N., Lyles, C., Radcliffe, K., Pasick, R. J., Sawaya, G., Sarkar, U., & Centola, D. (2019). Social media as a tool to promote health awareness: results from an online cervical cancer prevention study. *Journal of Cancer Education, 34*(4), 819-822.

MacDonald, P. L., & Gardner, R. C. (2000). Type I error rate comparisons of post hoc procedures for I j Chi-Square tables. *Educational and Psychological Measurement, 60*(5), 735-754.

Mangham, L. J., Hanson, K., & McPake, B. (2009). How to do (or not to do)… Designing a discrete choice experiment for application in a low-income country. *Health Policy and Planning, 24*(2), 151-158.

Mann, C. (2003). Observational research methods. Research design II: cohort, cross sectional, and case-control studies. *Emergency Medicine Journal, 20*(1), 54-60.

Mariel, P., Hoyos, D., Meyerhoff, J., Czajkowski, M., Dekker, T., Glenk, K., Jacobsen, J. B., Liebe, U., Olsen, S. B., & Sagebiel, J. (2021). *Environmental valuation with discrete choice experiments: Guidance on design, implementation and data analysis*. Springer Nature.

Markerly. (2015). *Instagram Marketing: Does Influencer Size Matter?* Markerly. https://markerly.com/blog/instagram-marketing-does-influencer-size-matter/

Martin, A., & Pietsch, J. (2013). Future shock or future stability?: Generational change and the Australian party system. *Australian Journal of Politics & History, 59*(2), 212-221.

Marwick, A. E. (2005). 'I'ma Lot More Interesting than a Friendster Profile': Identity Presentation, Authenticity and Power in Social Networking Services. *Association of Internet Researchers, 6*.

Masuda, H., Han, S. H., & Lee, J. (2022). Impacts of influencer attributes on purchase intentions in social media influencer marketing: Mediating roles of characterizations. *Technological Forecasting and Social Change, 174*, 121246.
McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior.
McFadden, D. (1986). The choice theory approach to market research. *Marketing science, 5*(4), 275-297.
Mediakix. (2019). *5 Top Brands Launching Micro-influencer Campaigns* Mediakix. https://mediakix.com/blog/micro-influencer-campaigns/
Mehmet, M., Roberts, R., & Nayeem, T. (2020). Using digital and social media for health promotion: A social marketing approach for addressing co-morbid physical and mental health. *Australian Journal of Rural Health, 28*(2), 149-158.
Merino-Castello, A. (2003). Eliciting consumers preferences using stated preference discrete choice models: contingent ranking versus choice experiment. *UPF economics and business working paper*(705).
Moran, G., Muzellec, L., & Johnson, D. (2019). Message content features and social media engagement: evidence from the media industry. *Journal of Product & Brand Management, 29*(5), 533-545.
Muench, F., van Stolk-Cooke, K., Morgenstern, J., Kuerbis, A. N., & Markle, K. (2014). Understanding messaging preferences to inform development of mobile goal-directed behavioral interventions. *Journal of medical Internet research, 16*(2), e14.
Mukti, O. F. W., & Putri, N. K. (2021). Social Media Analytics: Instagram Utilization for Delivering Health Education Messages to Young Adult in Indonesia. *Jurnal Promkes: The Indonesian Journal of Health Promotion and Health Education, 9*(1), 35-43.
National Statement on Ethical Conduct in Human Research 2007 (Updated 2018). The National Health and Medical Research Council, the Australian Research Council, Universities Australia. Commonwealth of Australia, Canberra.
Naylor, R. W., Lamberton, C. P., & West, P. M. (2012). Beyond the "like" button: The impact of mere virtual presence on brand evaluations and purchase intentions in social media settings. *Journal of Marketing, 76*(6), 105-120.
Nguyen, C., & Nguyen, D. (2020). A study of factors affecting brand awareness in the context of viral marketing in Vietnam. *International Journal of Advanced Science and Technology, 29*(5), 5401-5411.
Nguyen, M. H., Hunsaker, A., & Hargittai, E. (2020). Older adults' online social engagement and social capital: the moderating role of Internet skills. *Information, Communication & Society*, 1-17.
Nobles, J., Thomas, C., Banks Gross, Z., Hamilton, M., Trinder-Widdess, Z., Speed, C., Gibson, A., Davies, R., Farr, M., & Jago, R. (2020). "Let's Talk about Physical Activity": Understanding the Preferences of Under-Served Communities when Messaging Physical Activity Guidelines to the Public. *International Journal of Environmental Research and Public Health, 17*(8), 2782.
Noel, J. K., Babor, T. F., & Grady, J. J. (2018). Advertising content, platform characteristics and the appeal of beer advertising on a social networking site. *Alcohol and Alcoholism, 53*(5), 619-625.
O'Reilly, M., Dogra, N., Hughes, J., Reilly, P., George, R., & Whiteman, N. (2019). Potential of social media in promoting mental health in adolescents. *Health Promotion International, 34*(5), 981-991.
Office for Ageing Well. (2019). *Age Friendly SA Strategy*. Government of South Australia.

Ohanian, R. (1991). The impact of celebrity spokespersons' perceived image on consumers' intention to purchase. *Journal of Advertising Research*.

Olsen, C. Ø., & Sandholmen, G. M. (2019). *The dark side of influencer marketing* Handelshøyskolen BI.

Oluboyede, Y., Ternent, L., Vale, L., & Allen, J. (2019). Using a discrete-choice experiment to estimate the preferences of clinical practitioners for a novel non-invasive device for diagnosis of peripheral arterial disease in primary care. *PharmacoEconomics-open, 3*(4), 571-581.

Olum, R., & Bongomin, F. (2020). Social Media Platforms for Health Communication and Research in the Face of COVID-19 Pandemic: A Cross Sectional Survey in Uganda. *medRxiv*.

Pagoto, S., Waring, M. E., & Xu, R. (2019). A call for a public health agenda for social media research. *Journal of Medical Internet Research, 21*(12).

Park, S., Fisher, C., McGuinness, K., Lee, J. Y., & McCallum, K. (2021). *Digital news report: Australia 2021* [Report]. News and Media Research Centre, University of Canberra. https://doi.org/10.25916/kygy-s066

Park, Y. S., Konge, L., & Artino Jr, A. R. (2020). The positivism paradigm of research. *Academic Medicine, 95*(5), 690-694.

Păvăloaia, V.-D., Teodor, E.-M., Fotache, D., & Danileţ, M. (2019). Opinion mining on social media data: sentiment analysis of user preferences. *Sustainability, 11*(16), 4459.

Pedersen, E. A., Loft, L. H., Jacobsen, S. U., Søborg, B., & Bigaard, J. (2020). Strategic health communication on social media: Insights from a Danish social media campaign to address HPV vaccination hesitancy. *Vaccine, 38*(31), 4909-4915.

Pedroni, M. (2016). Meso-celebrities, fashion and the media: How digital influencers struggle for visibility. *Film, Fashion & Consumption., 5*(1), 103-121. https://doi.org/10.1386/ffc.5.1.103_1

Pérez-Troncoso, D. (2020). A step-by-step guide to design, implement, and analyze a discrete choice experiment.

Pew Research Center. (2019). *Social Media Fact Sheet*. https://www.pewresearch.org/internet/fact-sheet/social-media/

Pew Research Center. (2020). *53% of Americans Say the Internet Has Been Essential During the COVID-19 Outbreak*. https://www.pewresearch.org/internet/2020/04/30/53-of-americans-say-the-internet-has-been-essential-during-the-covid-19-outbreak/

Plantin, J.-C., & Punathambekar, A. (2019). Digital media infrastructures: pipes, platforms, and politics. *Media, Culture & Society, 41*(2), 163-174.

Polger, M. A., & Sich, D. (2019). Are they even following us? Using market research data to understand students' social media preferences. *Library Management, 40*(8/9), 503-517.

Pöyry, E., Reinikainen, H., & Luoma-Aho, V. (2022). The Role of Social Media Influencers in Public Health Communication: Case COVID-19 Pandemic. *International Journal of Strategic Communication, 16*(3), 469-484.

Qin, Y. S. (2020). Fostering brand–consumer interactions in social media: the role of social media uses and gratifications. *Journal of Research in Interactive Marketing, 14*(3), 337-354.

Qualtrics XM. (2022). Qualtrics (December 2021) [Computer software]. https://www.qualtrics.com

Rainie, L. (2018). *Americans' complicated feelings about social media in an era of privacy concerns.* https://www.pewresearch.org/fact-tank/2018/03/27/americans-complicated-feelings-about-social-media-in-an-era-of-privacy-concerns/

Rus, H. M., & Cameron, L. D. (2016). Health communication in social media: message features predicting user engagement on diabetes-related Facebook pages. *Annals of behavioral medicine, 50*(5), 678-689.

Ryan, M., Gerard, K., & Amaya-Amaya, M. (2008). Discrete choice experiments in a nutshell. In *Using discrete choice experiments to value health and health care* (pp. 13-46). Springer.

Sanny, L., Arina, A., Maulidya, R., & Pertiwi, R. (2020). Purchase intention on Indonesia male's skin care by social media marketing effect towards brand image and brand trust. *Management Science Letters, 10*(10), 2139-2146.

Saravanakumar, M., & SuganthaLakshmi, T. (2012). Social media marketing. *Life Science Journal, 9*(4), 4444-4451.

SAS Institute. (2022). SAS (Version 9.4M7) [Computer software]. https://www.sas.com/en_au/

Schouten, A. P., Janssen, L., & Verspaget, M. (2020). Celebrity vs. Influencer endorsements in advertising: the role of identification, credibility, and Product-Endorser fit. *International Journal of Advertising, 39*(2), 258-281.

Schultz, D. E., & Peltier, J. J. (2013). Social media's slippery slope: challenges, opportunities and future research directions. *Journal of Research in Interactive Marketing*.

Seetharaman, P. (2020). Business models shifts: Impact of Covid-19. *International Journal of Information Management, 54*, 102173.

Shah, A. M., Zahoor, S. Z., & Qureshi, I. H. (2019). Social Media and Purchasing Behavior: A Study of the Mediating Effect of Customer Relationships. *Journal of Global Marketing, 32*(2), 93-115.

Shahbaznezhad, H., Dolan, R., & Rashidirad, M. (2021). The Role of Social Media Content Format and Platform in Users' Engagement Behavior. *Journal of Interactive Marketing, 53*, 47-65.

Shahbaznezhad, H., Dolan, R., & Rashidirad, M. (2021). The Role of Social Media Content Format and Platform in Users' Engagement Behavior. *Journal of Interactive Marketing, 53*, 47-65.

Shane-Simpson, C., Manago, A., Gaggi, N., & Gillespie-Lynch, K. (2018). Why do college students prefer Facebook, Twitter, or Instagram? Site affordances, tensions between privacy and self-expression, and implications for social capital. *Computers in Human Behavior, 86*, 276-288.

Silva, S. C., Feitosa, W., Duarte, P., & Vasconcelos, M. (2020). How to increase engagement on social media using the honeycomb model A case study in a Portuguese HR company. *REGE Revista de Gestão, 27*(2), 153-167.

Socially Powerful Media. (2018). *How Luxury Fashion Brands are Leveraging Social Media and Influencer Marketing: Social Media and Influencer Marketing Performance Benchmarking Report*. https://static1.squarespace.com/static/558bbd9ee4b04e1adcef710e/t/5bb20a7ceef1a191b6619adb/1538394759775/Socially+Powerful++Luxury+Fashion+Presentation_Email+optimised.pdf

Soto-Vásquez, A. D., & Jimenez, N. (2022). Nano-& Micro-Influencers. In *The Emerald Handbook of Computer-Mediated Communication and Social Media* (pp. 305-321). Emerald Publishing Limited.

Spector, P. E. (2019). Do not cross me: Optimizing the use of cross-sectional designs. *Journal of Business and Psychology, 34*(2), 125-137.

StataCorp. (2022). Stata (Version 17.0) [Computer software]. https://www.stata.com

Stellefson, M., Paige, S. R., Chaney, B. H., & Chaney, J. D. (2020). Evolving role of social media in health promotion: Updated responsibilities for health education specialists. *International journal of environmental research and public health, 17*(4), 1153.

Stikker, P. (2022). *Nominal vs. Nominal: Effect Size*. https://peterstatistics.com/CrashCourse/3-TwoVarUnpair/NomNom/NomNom-2c-Effect-Size.html

Stubb, C., & Colliander, J. (2019). "This is not sponsored content"–The effects of impartiality disclosure and e-commerce landing pages on consumer responses to social media influencer posts. *Computers in Human Behavior, 98*, 210-222.

Tafesse, W., & Wien, A. (2018). Using message strategy to drive consumer behavioral engagement on social media. *Journal of Consumer Marketing, 58,* 102303.

Tafheem, N., El-Gohary, H., & Sobh, R. (2022). Social media user-influencer congruity: An analysis of social media platforms parasocial relationships. *International Journal of Customer Relationship Marketing and Management (IJCRMM), 13*(1), 1-26.

Thach, L., Riewe, S., & Camillo, A. (2021). Generational cohort theory and wine: analyzing how gen Z differs from other American wine consuming generations. *International Journal of Wine Business Research, 33*(1), 1-27.

Thackeray, R., Neiger, B. L., Smith, A. K., & Van Wagenen, S. B. (2012). Adoption and use of social media among public health departments. *BMC Public Health, 12*(1), 242-242. https://doi.org/10.1186/1471-2458-12-242

Thurstone, L. L. (1927). A law of comparative judgment. *Psychological Review, 34*(4), 273.

Trifiro, B. M., & Gerson, J. (2019). Social media usage patterns: Research note regarding the lack of universal validated measures for active and passive use. *Social Media+ Society, 5*(2), 2056305119848743.

Trivedi, J. P. (2018). Measuring the comparative efficacy of an attractive celebrity influencer vis-à-vis an expert influencer-a fashion industry perspective. *International Journal of Electronic Customer Relationship Management, 11*(3), 256-271.

Trziszka, M. (2021). Micro-influencers as an Effective Channel to Reach Customers Using Social Media in the Time of the COVID-19 Pandemic. In S. Trzcielinski, B. Mrugalska, W. Karwowski, E. Rossi, & M. Di Nicolantonio, *Advances in Manufacturing, Production Management and Process Control* Cham.

Turner, M. J., & Coote, L. V. (2017). Discrete choice experiments: a research agenda for experimental accounting. *Meditari Accountancy Research*.

Valkenburg, P. M., van Driel, I. I., & Beyens, I. (2022). The associations of active and passive social media use with well-being: A critical scoping review. *New Media & Society, 24*(2), 530-549.

Vanniyasingam, T., Cunningham, C. E., Foster, G., & Thabane, L. (2016). Simulation study to determine the impact of different design features on design efficiency in discrete choice experiments. *BMJ open, 6*(7).

Vanniyasingam, T., Daly, C., Jin, X., Zhang, Y., Foster, G., Cunningham, C., & Thabane, L. (2018). Investigating the impact of design characteristics on statistical efficiency

within discrete choice experiments: A systematic survey. *Contemporary Clinical Trials Communications, 10*, 17-28. https://doi.org/https://doi.org/10.1016/j.conctc.2018.01.002

Verduyn, P., Ybarra, O., Résibois, M., Jonides, J., & Kross, E. (2017). Do social network sites enhance or undermine subjective well-being? A critical review. *Social Issues and Policy Review, 11*(1), 274-302.

Vinerean, S. (2017). Importance of strategic social media marketing. *Expert Journal of Marketing, 5*(1), 28-35.

Vogels, E. A. (2019). *Millennials stand out for their technology use, but older generations also embrace digital life*. Pew Research Center. https://www.pewresearch.org/fact-tank/2019/09/09/us-generations-technology-use/

Voorveld, H. A., Van Noort, G., Muntinga, D. G., & Bronner, F. (2018). Engagement with social media and social media advertising: The differentiating role of platform type. *Journal of Advertising, 47*(1), 38-54.

Wang, R., Kim, J., Xiao, A., & Jung, Y. J. (2017). Networked narratives on Humans of New York: A content analysis of social media engagement on Facebook. *Computers in Human Behavior, 66*, 149-153.

We Are Social. (2022a). *Digital 2022 Australia: Online Like Never Before* (Digital 2022, Issue. https://wearesocial.com/au/blog/2022/02/digital-2022-australia-online-like-never-before/

We Are Social. (2022b). *Digital 2022: Another Year of Bumper Growth* (Digital 2022, Issue. https://wearesocial.com/au/blog/2022/01/digital-2022-another-year-of-bumper-growth/

Webber, R. (2013). The evolution of direct, data and digital marketing. *Journal of Direct, Data and Digital Marketing Practice, 14*(4), 291-309.

Wellman, B., Salaff, J., Dimitrova, D., Garton, L., Gulia, M., & Haythornthwaite, C. (1996). Computer networks as social networks: Collaborative work, telework, and virtual community. *Annual review of sociology, 22*(1), 213-238.

Wilson, E. A., & Wolf, M. S. (2009). Working memory and the design of health materials: a cognitive factors perspective. *Patient education and counseling, 74*(3), 318-322.

World Health Organization. (2015). *World report on ageing and health*. World Health Organization.

World Health Organization. (2019, 30 September 2019). WHO launches digital app to improve care for older people. https://www.who.int/news/item/30-09-2019-who-launches-digital-app-to-improve-care-for-older-people

Wright, E., Khanfar, N. M., Harrington, C., & Kizer, L. E. (2010). The lasting effects of social media trends on advertising. *Journal of Business & Economics Research (JBER), 8*(11).

Xie, W., Damiano, A., & Jong, C.-H. (2022). Emotional appeals and social support in organizational YouTube videos during COVID-19. *Telematics and Informatics Reports, 8*, 100028.

Yap, J. (2018, August 20, 2018). What is D-Error? *DisplayR*. https://www.displayr.com/what-is-d-error/

Yates, D., Moore, D., & McCabe, G. (1999). *The Practice of Statistics.* (1st Edition ed.).

YPulse. (2020). *Gen Z & Millennials' 5 Favorite Social Media Platforms Now*. https://www.ypulse.com/article/2020/05/06/gen-z-millennials-5-favorite-social-media-platforms-now/

Yuan, S., Hussain, S. A., Hales, K. D., & Cotten, S. R. (2016). What do they like? Communication preferences and patterns of older adults in the United States: The role of technology. *Educational Gerontology, 42*(3), 163-174.

Zablotski, Y. (2019, December 31, 2019). Logistic regression 5: multiple logistic regression with interactions. *Dr. Yury Zablotski*. https://yury-zablotski.netlify.app/post/multiple-logistic-regression-with-interactions/

Zhang, K., Kim, K., Silverstein, N. M., Song, Q., & Burr, J. A. (2020). Social Media Communication and Loneliness Among Older Adults: The Mediating Roles of Social Support and Social Contact. *The Gerontologist,* 1-9.

Ziemba, E., & Eisenbardt, M. (2016). Incentives encouraging prosumers to knowledge sharing–framework based on Polish study. *Online Journal of Applied Knowledge Management (OJAKM), 4*(2), 146-166.

Zollo, L., Filieri, R., Rialti, R., & Yoon, S. (2020). Unpacking the relationship between social media marketing and brand equity: The mediating role of consumers' benefits and experience. *Journal of Business Research, 117*, 256-267.

Appendices

Appendix A: University of South Australia Ethics Approval

Dear Victoria

APPROVAL: REF: Negligible Risk Ethics Application: 056/2021: Victoria Taddeo: Let's get intimate: understanding the preferences of an age diverse audience in relation to micro-influencer message strategies

Thank you for submitting your Negligible Risk Ethics Application 056-2021

Your application has been reviewed by the UniSA Business Ethics Committee and we are pleased to advise it has been ***APPROVED*** with the following amendment to your consent/information form:

- ***Advise participants they can withdraw at any time***

Could you please amend your form and return to BIS-Research@unisa.edu.au for our records.

Your UniSA Ethics Number for the application is **056-2021** for your records and consent/participant information forms (if required)

As you have now received ethics approval, your research project may now proceed.

Kind regards,

UniSA Business Ethics Committee



Let's Get Intimate

Information Sheet

Let's get intimate: understanding the preferences of an age diverse audience in relation to micro-influencer message strategies

Thank you for taking the time to participate in this research. We know social media is becoming an important part of daily life and plays a critical role in sharing messages to an audience. Messages shared in the health and wellbeing space can appeal to audiences of diverse ages. This research seeks to understand what the preferences of an age diverse audience are in relation to messages that are shared by micro-influencers which can then assist micro-influencers to tailor essential health information for audiences at any stage of their life.

The following explains the processes involved with taking part. Knowing what is involved will help you decide if you want to participate in the research. Please read this information carefully and do not hesitate to ask questions about anything that you do not understand or would like to know more about.

***

To participate in this research, you must be at least 18 years of age and a social media user. Your participation in this survey will be confidential and anonymous and **will involve completing an online survey** which **will take approximately 15-20 minutes to complete**. The survey is comprised of seven sections to learn more about you; your social media use and activity; your understanding and following of micro-influencers; your social media platform preferences; and what preferences you have in social media message format and message type.

The information you provide will be anonymous and will be stored securely in locked and password protected folders on the university's server. It is not anticipated that there are any risks involved by participating in this study beyond those encountered in everyday life.

Although there will be no direct benefits for participating in this study, as a user of social media who may follow digital micro-influencers, this research will better equip micro-influencers to communicate with you in the way you prefer. For every participant who completes the survey, $1 will be donated to a health charity to reach a target of $500.

***

If you would like a summary of the results, you will be invited to provide an email address at the end of the survey. Your email address will be stored separately from your survey responses, which will maintain survey response anonymity, and will be stored securely in a password protected folder on the university server. This summary of results will be sent to

you at the completion of the research project.

***

The research is being organised and conducted by Victoria Taddeo as part of a Masters by Research project. The researcher has support through an Australian Government Research Training Program Scholarship.

The ethical aspects of this research project have been approved by the UniSA Business Ethics Committee (UniSA Ethics Number: 056-2021).

If you would like further information about this project or if you have any problems which may be related to your involvement in the project, you can contact the researcher (details below).

Researcher details

Victoria Taddeo: victoria.taddeo@mymail.unisa.edu.au
Allan O'Connor (Principal Supervisor): allan.oconnor@unisa.edu.au
UniSA Business Ethics Committee: Tel: 8302 0245, Email: BIS-Research@unisa.edu.au

Your participation in this research is voluntary and you do not have to participate if you do not want to. If you wish to withdraw after agreeing to participate, you can do so at any time.

By completing and submitting the survey you are indicating that you:

- ○ Understand what you have read
- ○ Consent to take part in the research project

Please note: When completing the survey do not press the back button on your browser, as some of your responses may not be recorded. If you close your browser window for any reason, you can return to the survey by clicking the survey link again. This should take you back to the survey page you were on.

I confirm I am **18 years of age or older**

- ○ Yes (1)
- ○ No (2)

ABOUT YOU

Q1
What is your age?

▼ 18 (1) ... 105+ (88)

Q2 Gender: How do you identify?

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary (3)
- ○ Prefer to self-describe (4)
  _____
- ○ Prefer not to say (5)

Q3 Are you an Australian citizen?

- ○ Yes (1)
- ○ No (2)

Q4 Do you identify as Aboriginal or Torres Strait Islander?

- ○ Yes (1)
- ○ No (2)
- ○ Prefer not to say (3)

Q5 Do you currently live in Australia?

- ○ Yes (1)
- ○ No (2)

Q6 What is your Postcode?

YOUR SOCIAL MEDIA USE

Q7 Social media provides users, including, individuals; firms; institutions; and organisations, a platform to interact and exchange information and user-generated content, including, a digital marketing channel for marketers to advertise and communicate with their consumers. Examples of social media platforms include Facebook, Instagram, YouTube, Twitter, and TikTok.

With this in mind please answer the following questions regarding your social media use and social media activity.

Do you have a social media account?

- ○ Yes (1)
- ○ No (2)
- ○ Unsure (3)
- ○ Prefer not to say (4)

Q8 Which social media platforms do you have an account with? *Please select all that apply.*

- ☐ Facebook (1)
- ☐ Facebook Messenger (2)
- ☐ Instagram (3)
- ☐ LinkedIn (4)
- ☐ Pinterest (5)
- ☐ Reddit (6)
- ☐ Skype (7)
- ☐ Snapchat (8)
- ☐ TikTok (9)
- ☐ Tumblr (10)
- ☐ Twitch (11)
- ☐ Twitter (12)

- [ ] Viber (13)
- [ ] WeChat (14)
- [ ] WhatsApp (15)
- [ ] YouTube (16)
- [ ] Other (17) _____

Q9 Would you consider yourself to be an active user of social media?
An active user is one who spends time on social media platforms and/or engages in direct

exchanges with other social media users. Examples of direct exchanges include liking, sending messages, commenting, and sharing messages through photos, videos, or text.

- ○ Yes (1)
- ○ No (2)
- ○ Unsure (3)

Carry Forward Selected Choices - Entered Text from "Q8"

Q11 What social media platform are you **most** active on? *Please select one.*

- ○ Facebook (1)
- ○ Facebook Messenger (2)
- ○ Instagram (3)
- ○ LinkedIn (4)
- ○ Pinterest (5)
- ○ Reddit (6)
- ○ Skype (7)
- ○ Snapchat (8)
- ○ TikTok (9)
- ○ Tumblr (10)
- ○ Twitch (11)
- ○ Twitter (12)
- ○ Viber (13)
- ○ WeChat (14)
- ○ WhatsApp (15)

- ○ YouTube (16)
- ○ Other (17)

Q9 On what type of device do you **most** access your social media account? *Please select one.*

- ○ Smartphone (1)
- ○ Tablet (2)
- ○ Laptop (3)
- ○ Desktop computer (4)
- ○ Wearable (e.g., smartwatch) (5)
- ○ Smart television (6)
- ○ Other (7) _____

Q12 At what time of the day are you **most** active on social media? *Please select one.*

- ○ Early morning (6:01am – 8am) (1)
- ○ Mid-morning (8:01am – 10am) (2)
- ○ Late morning (10:01am – 12pm) (3)
- ○ Early afternoon (12:01pm – 2pm) (4)
- ○ Mid-afternoon (2:01 – 4pm) (5)
- ○ Late afternoon (4:01pm – 6pm) (6)
- ○ Early evening (6:01pm – 8pm) (7)
- ○ Mid-evening (8:01pm – 10pm) (8)
- ○ Late evening (10:01pm – 12am) (9)
- ○ Overnight (12:01am – 6am) (10)

Q13 How often do you access social media? *Please select one.*

- ○ Constantly throughout the day (1)
- ○ More than 10 times per day (2)
- ○ About 5-10 times per day (3)
- ○ About 1-4 times per day (4)
- ○ Several times a week (5)
- ○ Once a week (6)
- ○ Once or twice a month (7)
- ○ Less than once a month (8)

Q14 When thinking about your social media use over the past week, what activities did you **most** use social media for? *Please select all that apply*.

- ☐ To stay updated with current affairs and news (1)
- ☐ Connect, communicate and stay in touch with people you know (2)
- ☐ Share photos, videos, stories (3)
- ☐ Meet new people (4)
- ☐ Pass the time (5)
- ☐ Watch videos (6)
- ☐ Find and connect with like-minded communities and interest groups (7)
- ☐ Discover and research new brands and products (8)

- [ ] Follow brands or organisations (9)
- [ ] Shop and make purchases (10)
- [ ] Play games (11)
- [ ] Organise or discover events (12)
- [ ] Follow celebrities and influencers (13)
- [ ] Inspiration and ideas (14)
- [ ] Read/write reviews (15)
- [ ] Promote a business (16)
- [ ] Customer service (17)
- [ ] Work-related networking (18)
- [ ] Work-related research (19)
- [ ] Other (20) _____

MICRO-INFLUENCERS

Q15 For the purpose of this survey, micro-influencers are digital influencers, also known as social media influencers, who have between 10,000 and 100,000 followers on a social media platform. Due to their smaller audience, micro-influencers typically have a greater capacity to connect and interact with their followers on a more intimate and personal level and can be considered to be more authentic and accessible to their audience.

With this in mind, please answer the following questions.

Do you follow any micro-influencers on social media?

- ○ Yes (1)
- ○ No (2)
- ○ Unsure (3)

Skip To: End of Block (which next question is Q17) If Q15 = Yes
Skip To: Q16 If Q15 = No
Skip To: Q16 If Q15 = Unsure

Q16
Micro-influencers are digital influencers, also known as social media influencers, who have between 10,000 and 100,000 followers on a social media platform. Due to their smaller audience, **micro-influencers** typically **have a greater capacity to connect and interact with their followers** on a more intimate and personal level and can be considered to be more authentic and accessible to their audience.
Based on the description of micro-influencers provided to you above, would you consider following a micro-influencer in the future?

- ○ Yes (1)
- ○ No (2)
- ○ Unsure (3)

Q17 Why do you follow micro-influencers? *Please select all that apply.*

- ☐ Discounts and promotions (1)
- ☐ Giveaways and competitions (2)
- ☐ Inspiration and ideas (3)
- ☐ Brand and product information (4)
- ☐ Reviews and opinions (5)
- ☐ Relaxing and entertaining content (6)
- ☐ Companionship (7)
- ☐ Other (8) _____

Q18 On what platforms do you follow micro-influencers? *Please select all that apply.*

- ☐ Facebook (1)
- ☐ Facebook Messenger (2)
- ☐ Instagram (3)
- ☐ LinkedIn (4)
- ☐ Pinterest (5)
- ☐ Reddit (6)

- [ ] Skype (7)
- [ ] Snapchat (8)
- [ ] TikTok (9)
- [ ] Tumblr (10)
- [ ] Twitch (11)
- [ ] Twitter (12)
- [ ] Viber (13)
- [ ] WeChat (14)
- [ ] WhatsApp (15)
- [ ] YouTube (16)
- [ ] Other (17) _____

Q19 Do you follow the same micro-influencer on more than one social media platform?
In other words, when thinking of a micro-influencer you follow, do you follow them on multiple social media platforms such as Instagram AND YouTube, not just one social media platform?

- ○ Yes (1)
- ○ No (2)

PREFERENCES OF SOCIAL MEDIA PLATFORM

Q20 The following sections seek to understand your preferences of social media platform, message format, and message type.

In a general sense, when using social media to view messages shared by micro-influencers, what social media platform do you, or would you, **most** prefer? *Please select one.*

- ○ Facebook (1)
- ○ Facebook Messenger (2)
- ○ Instagram (3)
- ○ LinkedIn (4)
- ○ Pinterest (5)
- ○ Reddit (6)
- ○ Skype (7)
- ○ Snapchat (8)
- ○ TikTok (9)
- ○ Tumblr (10)
- ○ Twitch (11)
- ○ Twitter (12)
- ○ Viber (13)
- ○ WeChat (14)
- ○ WhatsApp (15)
- ○ YouTube (16)
- ○ Other (17) _____

Q21 Why do you prefer ${Q20/ChoiceGroup/SelectedChoicesTextEntry}?

_____

PREFERENCES OF MESSAGE FORMAT

Q22 In a general sense, when using social media to view messages shared by micro-influencers, which of the following do you, or would you, **most** prefer? *Please select one.*

- ○ Written Text (1)
- ○ Video (2)
- ○ Picture (3)

Q23 When you are thinking about ${Q20/ChoiceGroup/SelectedChoicesTextEntry}, which of the following do you **most** prefer? *Please select one.*

- ○ Written Text (1)
- ○ Video (2)
- ○ Picture (3)

PREFERENCES OF MESSAGE TYPE

Q24 Message types can be classified into four main categories: informative, promotional, interactive, and emotional or relatable. Below are the four message types with a description and examples of each.

Q25 In a general sense, when using social media to view messages shared by micro-influencers, which of the following do you, or would you, **most** prefer? *Please select one.*

- ○ Informative (Inform or Educate) (1)
- ○ Promotional (Promote or Reward/Incentivise) (2)
- ○ Interactive (Involve or Interact) (3)
- ○ Emotional or relatable (Evoke emotion, relate to a social-cause, differentiate a brand/organisation) (4)

Q26 When you are thinking about ${Q20/ChoiceGroup/SelectedChoicesTextEntry}, which of the following do you **most** prefer? *Please select one.*

- ○ Informative (Inform or Educate) (1)
- ○ Promotional (Promote or Reward/Incentivise) (2)
- ○ Interactive (Involve or Interact) (3)
- ○ Emotional or relatable (Evoke emotion, relate to a social-cause, differentiate a brand/organisation) (4)

YOUR PREFERENCES

Q27 The final section of this survey comprises of 12 questions and aims to identify which combination of message format and message type you most prefer.

Although it may feel like the following questions are the same, you will be presented with different combinations of message strategies in each question. You will be asked to choose which message strategy you prefer out of the two.

Q28: Choice Set 1 When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

- ○ Promotional Text (5)
- ○ Interactive Picture (6)

Q29: Choice Set 2 When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

- ○ Informative Picture (1)
- ○ Emotional or Relatable Text (2)

Q30: Choice Set 3 When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

- ○ Emotional or Relatable Video (1)
- ○ Promotional Text (2)

Q31: Choice Set 4 When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

- ○ Interactive Video (1)
- ○ Informative Text (2)

Q32: Choice Set 5 When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

- ○ Emotional or Relatable Picture (1)
- ○ Interactive Video (2)

Q33: Choice Set 6 When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

- ○ Promotional Picture (1)
- ○ Interactive Text (2)

Q34: Choice Set 7 When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

- ○ Informative Picture (1)
- ○ Emotional or Relatable Text (2)

Q35: Choice Set 8 When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

- ○ Informative Video (1)
- ○ Interactive Picture (2)

Q36: Choice Set 9 When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

- ○ Emotional or Relatable Picture (1)
- ○ Promotional Video (2)

Q37: Choice Set 10 When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

- ○ Interactive Text (1)
- ○ Emotional or Relatable Video (2)

Q38: Choice Set 11 When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

- ○ Informative Text (1)
- ○ Promotional Video (2)

Q39: Choice Set 12 When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

- ○ Promotional Picture (1)
- ○ Informative Video (2)

Q40 Are your message strategy preferences likely to differ depending on the topic of the message?
In other words, if the message focused on a topic other than health and wellbeing such as gaming, fashion, parenting, travel, or beauty, would your message strategy preferences differ?

- ○ Yes (please tell us why) (1)
  _____
- ○ No (please tell us why) (2)
  _____
- ○ Unsure (3)

Appendix C: Discrete Choice Experiment Presentation in Survey

Choice Set 1

When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

Promotional	**Interactive**
 TEXT	 PICTURE
Written text that promotes or rewards/incentivises	*A picture that invites you to get involved or interact*
For example: • *Opportunity to win something e.g., giveaways* • *Offering discount codes, special offers or deals* • *Paid partnership/sponsorship with brands or organisations*	*For example:* • *Asking audience opinions about a topic, product, and/or service* • *Q&A's* • *Encourage audience to get involved in an activity or conversation* • *Entertainment*
❍	❍

Choice Set 2

When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

Informative	**Emotional or Relatable**
 PICTURE	 TEXT
A picture that informs or educates	*Written text that evokes emotion, relates to a social-cause, or differentiates a brand/organisation*
For example: • *Review product or service (not sponsored)* • *Provide information about a topic, brand or organisation, product, and/or service (not sponsored)* • *Provide resources such as links to information, products, or services (not sponsored)*	*For example:* • *Discuss emotional topics* • *Discuss a current event* • *Relate to a social-cause, e.g., COVID-19 Vaccine, fundraiser for health foundations or charities*
❍	❍

Choice Set 3

When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

Emotional or Relatable	**Promotional**
	
VIDEO	TEXT
A video that evokes emotion, relates to a social-cause, or differentiates a brand/organisation	*Written text that promotes or rewards/incentivises*
For example: • *Discuss emotional topics* • *Discuss a current event* • *Relate to a social-cause, e.g., COVID-19 Vaccine, fundraiser for health foundations or charities*	*For example:* • *Opportunity to win something e.g., giveaways* • *Offering discount codes, special offers or deals* • *Paid partnership/sponsorship with brands or organisations*
❍	❍

Choice Set 4

When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

Interactive	**Informative**
	
VIDEO	TEXT
A video that invites you to get involved or interact	*Written text that informs or educates*
For example: • *Asking audience opinions about a topic, product, and/or service* • *Q&A's* • *Encourage audience to get involved in an activity or conversation* • *Entertainment*	*For example:* • *Review product or service (not sponsored)* • *Provide information about a topic, brand or organisation, product, and/or service (not sponsored)* • *Provide resources such as links to information, products, or services (not sponsored)*
❍	❍

Choice Set 5

When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?	
Emotional or Relatable  PICTURE *A picture that evokes emotion, relates to a social-cause, or differentiates a brand/organisation* *For example:* • *Discuss emotional topics* • *Discuss a current event* • *Relate to a social-cause, e.g., COVID-19 Vaccine, fundraiser for health foundations or charities* ❍	**Interactive**  VIDEO *A video that invites you to get involved or interact* *For example:* • *Asking audience opinions about a topic, product, and/or service* • *Q&A's* • *Encourage audience to get involved in an activity or conversation* • *Entertainment* ❍

Choice Set 6

When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?	
Promotional  PICTURE *A picture that promotes or rewards/incentivises* *For example:* • *Opportunity to win something e.g., giveaways* • *Offering discount codes, special offers or deals* • *Paid partnership/sponsorship with brands or organisations* ❍	**Interactive**  TEXT *Written text that invites you to get involved or interact* *For example:* • *Asking audience opinions about a topic, product, and/or service* • *Q&A's* • *Encourage audience to get involved in an activity or conversation* • *Entertainment* ❍

Choice Set 7

When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?	
Informative  PICTURE *A picture that informs or educates* *For example:* • *Review product or service (not sponsored)* • *Provide information about a topic, brand or organisation, product, and/or service (not sponsored)* • *Provide resources such as links to information, products, or services (not sponsored)* ❍	**Emotional or Relatable**  TEXT *Written text that evokes emotion, relates to a social-cause, or differentiates a brand/organisation* *For example:* • *Discuss emotional topics* • *Discuss a current event* • *Relate to a social-cause, e.g., COVID-19 Vaccine, fundraiser for health foundations or charities* ❍

Choice Set 8

When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?	
Informative  VIDEO *A video that informs and educates* *For example:* • *Review product or service (not sponsored)* • *Provide information about a topic, brand or organisation, product, and/or service (not sponsored)* • *Provide resources such as links to information, products, or services (not sponsored)* ❍	**Interactive**  PICTURE *A picture that invites you to get involved or interact* *For example:* • *Asking audience opinions about a topic, product, and/or service* • *Q&A's* • *Encourage audience to get involved in an activity or conversation* • *Entertainment* ❍

Choice Set 9

When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

Emotional or Relatable	**Promotional**
 PICTURE	 VIDEO
A picture that evokes emotion, relates to a social-cause, or differentiates a brand/organisation	*A video that promotes or rewards/incentivises*
For example: • *Discuss emotional topics* • *Discuss a current event* • *Relate to a social-cause, e.g., COVID-19 Vaccine, fundraiser for health foundations or charities*	*For example:* • *Opportunity to win something e.g., giveaways* • *Offering discount codes, special offers or deals* • *Paid partnership/sponsorship with brands or organisations*
❍	❍

Choice Set 10

When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?

Interactive	**Emotional or Relatable**
 TEXT	 VIDEO
Written text that invites you to get involved or interact	*A video that evokes emotion, relates to a social-cause, or differentiates a brand/organisation*
For example: • *Asking audience opinions about a topic, product, and/or service* • *Q&A's* • *Encourage audience to get involved in an activity or conversation* • *Entertainment*	*For example:* • *Discuss emotional topics* • *Discuss a current event* • *Relate to a social-cause, e.g., COVID-19 Vaccine, fundraiser for health foundations or charities*
❍	❍

Choice Set 11

When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?	
Informative  TEXT *Written text that informs or educates* *For example:* • *Review product or service (not sponsored)* • *Provide information about a topic, brand or organisation, product, and/or service (not sponsored)* • *Provide resources such as links to information, products, or services (not sponsored)* ❍	**Promotional**  VIDEO *A video that promotes or rewards/incentivises* *For example:* • *Opportunity to win something e.g., giveaways* • *Offering discount codes, special offers or deals* • *Paid partnership/sponsorship with brands or organisations* ❍

Choice Set 12

When **micro-influencers** share **health and wellbeing messages** on social media, which would you **prefer to see**?	
Promotional  PICTURE *A picture that promotes or rewards/incentivises* *For example:* • *Opportunity to win something e.g., giveaways* • *Offering discount codes, special offers or deals* • *Paid partnership/sponsorship with brands or organisations* ❍	**Informative**  VIDEO *A video that informs and educates* *For example:* • *Review product or service (not sponsored)* • *Provide information about a topic, brand or organisation, product, and/or service (not sponsored)* • *Provide resources such as links to information, products, or services (not sponsored)* ❍

Appendix D: Recruitment Material

Facebook & LinkedIn Posts (on newsfeeds and Facebook groups)

Hi everyone,

I need your help!

I am looking for people over 18yrs to complete a 10-15 minute anonymous online survey for my Masters research study about effective ways social media (micro) influencers can deliver messages about health and wellbeing.

For every person who completes the survey, $1 will be donated to the National Breast Cancer Foundation.

I need at least 300 people to complete my survey so PLEASE click the following link to participate.

https://doit.az1.qualtrics.com/jfe/form/SV_2ujmBxnXhjSVZOe

Thank you all for your help, I really appreciate it!

***

Thank you so much to everyone who has completed my survey for my Masters research so far!

I still need at least 200 people over 18yrs so if you can spare 10-15 minutes to do the anonymous online survey linked below that would be so so appreciated!

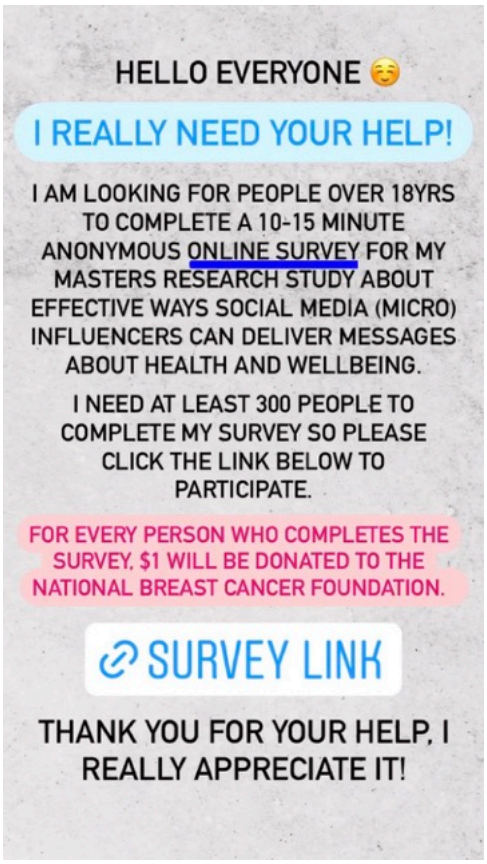
https://doit.az1.qualtrics.com/jfe/form/SV_2ujmBxnXhjSVZOe

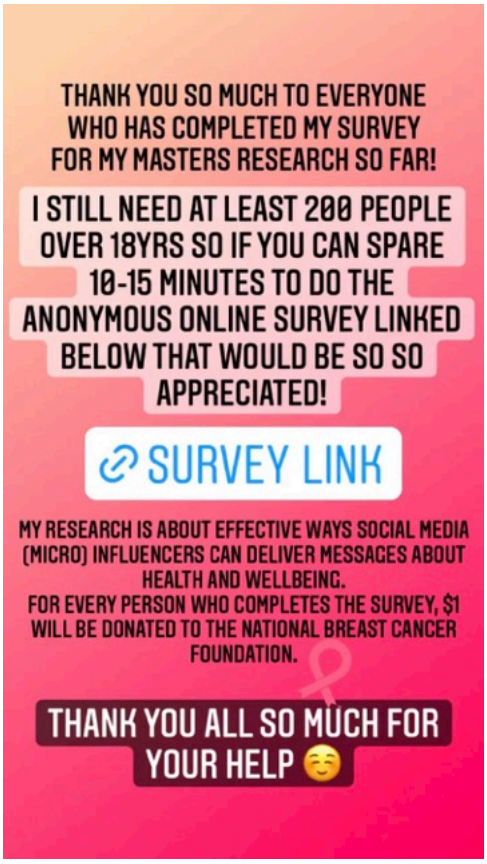
My research is about effective ways social media (micro) influencers can deliver messages about health and wellbeing.

For every person who completes the survey, $1 will be donated to the National Breast Cancer Foundation.

Thank you all so much for your help :)

Instagram Stories





Direct Message to Micro-influencers

Hi ——,

My name is Victoria Taddeo and I have been following you for quite some time, I love your content!

I am currently doing my Masters by Research at the University of South Australia and my survey topic is about effective ways social media (micro) influencers can deliver messages about health and wellbeing.

I am looking for about 300 people over 18yrs to complete a 10-15 minute anonymous online survey and was wondering if you could complete it for me, and if you could also share it that would be amazing. My research has UniSA approval and for every survey completed $1 will be donated to the National Breast Cancer Foundation. Here is the link to the survey: https://doit.az1.qualtrics.com/jfe/form/SV_2ujmBxnXhjSVZOe

As a big thank you, upon completion of my thesis this year, I can provide you with a detailed report about my findings.

If you are not able to that is okay and thank you for your time 😊

QR Code Flyer (face-to-face recruitment)

Dear Victoria

APPROVAL: REF: Negligible Risk Ethics Application: 056/2021: Victoria Taddeo: Let's get intimate: understanding the preferences of an age diverse audience in relation to micro-influencer message strategies

Thank you for submitting your Negligible Risk Ethics Application 056-2021

Your application has been reviewed by the UniSA Business Ethics Committee and we are pleased to advise it has been ***APPROVED*** with the following amendment to your consent/information form:

- ***Advise participants they can withdraw at any time***

Could you please amend your form and return to BIS-Research@unisa.edu.au for our records.

Your UniSA Ethics Number for the application is **056-2021** for your records and consent/participant information forms (if required)

As you have now received ethics approval, your research project may now proceed.

Kind regards,

UniSA Business Ethics Committee



Appendix E: SAS Output

The SAS System

Design Summary

Number of Levels	Frequency
3	1
4	1

The SAS System

Saturated = 6
Full Factorial = 12

Some Reasonable Design Sizes	Violations	Cannot Be Divided By
12 *	0	
6 S	2	4 12
8	2	3 12
9	2	4 12
7	3	3 4 12
10	3	3 4 12
11	3	3 4 12

* - 100% Efficient design can be made with the MktEx macro.
S - Saturated Design - The smallest design that can be made.

The SAS System

n	Design	Reference
12	3 ** 1 4 ** 1	Full-Factorial

The SAS System

Algorithm Search History

Design	Row,Col	Current D-Efficiency	Best D-Efficiency	Notes
1	Start	100.0000	100.0000	Tab
1	End	100.0000		

The SAS System

The OPTEX Procedure

Class Level Information

Class	Levels	Values
x1	3	1 2 3
x2	4	1 2 3 4

The SAS System

Design Number	D-Efficiency	A-Efficiency	G-Efficiency	Average Prediction Standard Error
1	100.0000	100.0000	100.0000	0.7071

The SAS System

Obs	x1	x2
1	1	1
2	1	2
3	1	3
4	1	4
5	2	1
6	2	2
7	2	3
8	2	4
9	3	1
10	3	2
11	3	3
12	3	4

The SAS System

n	Name	Beta	Label
1	x11	0	x1 1
2	x12	0	x1 2
3	x21	0	x2 1
4	x22	0	x2 2
5	x23	0	x2 3

The SAS System

Design	Iteration	D-Efficiency	D-Error
1	0	4.01204 *	0.24925
	1	8.27838 *	0.12080
	2	8.27838	0.12080

Design	Iteration	D-Efficiency	D-Error
2	0	3.34456	0.29899
	1	8.20732	0.12184
	2	8.28010 *	0.12077
	3	8.28010	0.12077

Design	Iteration	D-Efficiency	D-Error
3	0	3.79750	0.26333
	1	8.28756 *	0.12066
	2	8.28756	0.12066

Design	Iteration	D-Efficiency	D-Error
4	0	6.60263	0.15145
	1	8.31485 *	0.12027
	2	8.35069 *	0.11975

Design	Iteration	D-Efficiency	D-Error
5	0	4.51187	0.22164
	1	8.19927	0.12196
	2	8.35069	0.11975
	3	8.35069	0.11975

The SAS System

Design	Iteration	D-Efficiency	D-Error
6	0	4.11122	0.24324
	1	8.31485	0.12027
	2	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
7	0	5.29391	0.18890
	1	8.35069	0.11975
	2	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
8	0	4.12063	0.24268
	1	8.28756	0.12066
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
9	0	4.73336	0.21127
	1	8.21771	0.12169
	2	8.31485	0.12027
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
10	0	4.58443	0.21813
	1	8.20732	0.12184
	2	8.31485	0.12027
	3	8.31485	0.12027

The SAS System

Design	Iteration	D-Efficiency	D-Error
11	0	4.04282	0.24735
	1	8.27838	0.12080
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
12	0	5.38042	0.18586
	1	8.17433	0.12233
	2	8.28756	0.12066
	3	8.28756	0.12066

Design	Iteration	D-Efficiency	D-Error
13	0	4.02755	0.24829
	1	8.28010	0.12077
	2	8.28756	0.12066

Design	Iteration	D-Efficiency	D-Error
14	0	4.59356	0.21770
	1	8.21771	0.12169
	2	8.31485	0.12027
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
15	0	3.15074	0.31739
	1	8.31485	0.12027
	2	8.35069	0.11975

The SAS System

Design	Iteration	D-Efficiency	D-Error
16	0	5.63404	0.17749
	1	8.24359	0.12131
	2	8.24359	0.12131

Design	Iteration	D-Efficiency	D-Error
17	0	6.54773	0.15272
	1	8.31485	0.12027
	2	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
18	0	4.11122	0.24324
	1	8.24359	0.12131
	2	8.28756	0.12066
	3	8.35069	0.11975
	4	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
19	0	0	.
	1	8.27089	0.12091
	2	8.28756	0.12066

Design	Iteration	D-Efficiency	D-Error
20	0	4.82395	0.20730
	1	8.17946	0.12226
	2	8.31485	0.12027
	3	8.31485	0.12027

The SAS System

Design	Iteration	D-Efficiency	D-Error
21	0	5.63805	0.17737
	1	8.31485	0.12027
	2	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
22	0	3.90195	0.25628
	1	8.21148	0.12178
	2	8.31485	0.12027
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
23	0	4.18419	0.23899
	1	8.27838	0.12080
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
24	0	4.15742	0.24053
	1	8.20285	0.12191
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
25	0	4.44129	0.22516
	1	8.31485	0.12027
	2	8.31485	0.12027

The SAS System

Design	Iteration	D-Efficiency	D-Error
26	0	4.58443	0.21813
	1	8.23891	0.12138
	2	8.31485	0.12027
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
27	0	5.54270	0.18042
	1	8.28756	0.12066
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
28	0	4.66698	0.21427
	1	8.17130	0.12238
	2	8.38593 *	0.11925
	3	8.38593	0.11925

Design	Iteration	D-Efficiency	D-Error
29	0	5.09370	0.19632
	1	8.24301	0.12131
	2	8.38593	0.11925
	3	8.38593	0.11925

Design	Iteration	D-Efficiency	D-Error
30	0	5.15440	0.19401
	1	8.21534	0.12172
	2	8.24359	0.12131

The SAS System

Design	Iteration	D-Efficiency	D-Error
31	0	4.00156	0.24990
	1	8.18669	0.12215
	2	8.31485	0.12027
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
32	0	4.13919	0.24159
	1	8.22951	0.12151
	2	8.31485	0.12027
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
33	0	4.61161	0.21684
	1	8.24593	0.12127
	2	8.28756	0.12066
	3	8.28756	0.12066

Design	Iteration	D-Efficiency	D-Error
34	0	5.63538	0.17745
	1	8.31485	0.12027
	2	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
35	0	5.34781	0.18699
	1	8.22981	0.12151
	2	8.22981	0.12151

The SAS System

Design	Iteration	D-Efficiency	D-Error
36	0	3.01648	0.33151
	1	8.24301	0.12131
	2	8.38593	0.11925
	3	8.38593	0.11925

Design	Iteration	D-Efficiency	D-Error
37	0	3.94189	0.25369
	1	8.28756	0.12066
	2	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
38	0	4.54715	0.21992
	1	8.24359	0.12131
	2	8.28010	0.12077

Design	Iteration	D-Efficiency	D-Error
39	0	5.11360	0.19556
	1	8.24301	0.12131
	2	8.38593	0.11925
	3	8.38593	0.11925

Design	Iteration	D-Efficiency	D-Error
40	0	4.58137	0.21828
	1	8.14969	0.12270
	2	8.31485	0.12027
	3	8.35069	0.11975

The SAS System

Design	Iteration	D-Efficiency	D-Error
41	0	6.33954	0.15774
	1	8.20583	0.12186
	2	8.38593	0.11925
	3	8.38593	0.11925

Design	Iteration	D-Efficiency	D-Error
42	0	3.66527	0.27283
	1	8.35069	0.11975
	2	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
43	0	4.51187	0.22164
	1	8.19329	0.12205
	2	8.28756	0.12066
	3	8.28756	0.12066

Design	Iteration	D-Efficiency	D-Error
44	0	3.89023	0.25705
	1	8.28756	0.12066
	2	8.28756	0.12066

Design	Iteration	D-Efficiency	D-Error
45	0	5.86146	0.17061
	1	8.27838	0.12080
	2	8.38593	0.11925
	3	8.38593	0.11925

The SAS System

Design	Iteration	D-Efficiency	D-Error
46	0	4.59961	0.21741
	1	8.10826	0.12333
	2	8.31485	0.12027
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
47	0	4.59659	0.21755
	1	8.22981	0.12151
	2	8.22981	0.12151

Design	Iteration	D-Efficiency	D-Error
48	0	3.91353	0.25552
	1	8.28756	0.12066
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
49	0	4.59659	0.21755
	1	8.28756	0.12066
	2	8.28756	0.12066

Design	Iteration	D-Efficiency	D-Error
50	0	4.84863	0.20624
	1	8.20345	0.12190
	2	8.35069	0.11975
	3	8.35069	0.11975

The SAS System

Design	Iteration	D-Efficiency	D-Error
51	0	4.06778	0.24583
	1	8.28756	0.12066
	2	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
52	0	4.37331	0.22866
	1	8.21771	0.12169
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
53	0	4.04282	0.24735
	1	8.31485	0.12027
	2	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
54	0	4.92897	0.20288
	1	8.28756	0.12066
	2	8.28756	0.12066
Design	Iteration	D-Efficiency	D-Error
55	0	4.88473	0.20472
	1	8.31485	0.12027
	2	8.35069	0.11975

The SAS System

Design	Iteration	D-Efficiency	D-Error
56	0	5.16962	0.19344
	1	8.18187	0.12222
	2	8.31485	0.12027
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
57	0	5.28529	0.18920
	1	8.27089	0.12091
	2	8.31485	0.12027
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
58	0	4.46531	0.22395
	1	8.26916	0.12093
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
59	0	5.88190	0.17001
	1	8.23891	0.12138
	2	8.28756	0.12066
	3	8.35069	0.11975
	4	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
60	0	5.30929	0.18835
	1	8.19568	0.12202
	2	8.35069	0.11975
	3	8.35069	0.11975

The SAS System

Design	Iteration	D-Efficiency	D-Error
61	0	4.58748	0.21798
	1	8.21771	0.12169
	2	8.27838	0.12080
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
62	0	4.91748	0.20336
	1	8.35069	0.11975
	2	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
63	0	5.59050	0.17887
	1	8.24301	0.12131
	2	8.31485	0.12027
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
64	0	4.36218	0.22924
	1	8.28756	0.12066
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
65	0	5.91646	0.16902
	1	8.21534	0.12172
	2	8.31485	0.12027
	3	8.31485	0.12027

The SAS System

Design	Iteration	D-Efficiency	D-Error
66	0	4.71983	0.21187
	1	8.27089	0.12091
	2	8.38593	0.11925
	3	8.38593	0.11925

Design	Iteration	D-Efficiency	D-Error
67	0	4.93581	0.20260
	1	8.23422	0.12144
	2	8.31485	0.12027
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
68	0	5.50353	0.18170
	1	8.27089	0.12091
	2	8.31485	0.12027
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
69	0	5.15822	0.19387
	1	8.31485	0.12027
	2	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
70	0	4.94262	0.20232
	1	8.27089	0.12091
	2	8.31485	0.12027
	3	8.31485	0.12027

The SAS System

Design	Iteration	D-Efficiency	D-Error
71	0	4.99358	0.20026
	1	8.24359	0.12131
	2	8.28756	0.12066
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
72	0	5.69821	0.17549
	1	8.21771	0.12169
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
73	0	5.05295	0.19790
	1	8.24359	0.12131
	2	8.24359	0.12131

Design	Iteration	D-Efficiency	D-Error
74	0	4.22734	0.23656
	1	8.19927	0.12196
	2	8.19927	0.12196

Design	Iteration	D-Efficiency	D-Error
75	0	5.45103	0.18345
	1	8.22981	0.12151
	2	8.22981	0.12151

The SAS System

Design	Iteration	D-Efficiency	D-Error
76	0	3.86636	0.25864
	1	8.19329	0.12205
	2	8.28756	0.12066
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
77	0	4.77563	0.20940
	1	8.24359	0.12131
	2	8.24359	0.12131

Design	Iteration	D-Efficiency	D-Error
78	0	5.64870	0.17703
	1	8.24359	0.12131
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
79	0	3.88432	0.25745
	1	8.30579	0.12040
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
80	0	4.77303	0.20951
	1	8.27838	0.12080
	2	8.35069	0.11975
	3	8.35069	0.11975

The SAS System

Design	Iteration	D-Efficiency	D-Error
81	0	4.17089	0.23976
	1	8.23422	0.12144
	2	8.24125	0.12134

Design	Iteration	D-Efficiency	D-Error
82	0	4.49546	0.22245
	1	8.28010	0.12077
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
83	0	5.04880	0.19807
	1	8.24301	0.12131
	2	8.31485	0.12027
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
84	0	5.51671	0.18127
	1	8.27089	0.12091
	2	8.31485	0.12027
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
85	0	3.82312	0.26157
	1	8.24301	0.12131
	2	8.31485	0.12027
	3	8.35069	0.11975

The SAS System

Design	Iteration	D-Efficiency	D-Error
86	0	4.61756	0.21656
	1	8.24359	0.12131
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
87	0	0	.
	1	8.22951	0.12151
	2	8.31485	0.12027
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
88	0	4.60262	0.21727
	1	8.19927	0.12196
	2	8.19927	0.12196

Design	Iteration	D-Efficiency	D-Error
89	0	5.44797	0.18355
	1	8.24301	0.12131
	2	8.28756	0.12066
	3	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
90	0	3.37632	0.29618
	1	8.27838	0.12080
	2	8.31485	0.12027

The SAS System

Design	Iteration	D-Efficiency	D-Error
91	0	3.52824	0.28343
	1	8.22981	0.12151
	2	8.22981	0.12151

Design	Iteration	D-Efficiency	D-Error
92	0	5.73112	0.17449
	1	8.31485	0.12027
	2	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
93	0	3.12285	0.32022
	1	8.31485	0.12027
	2	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
94	0	6.54111	0.15288
	1	8.28756	0.12066
	2	8.28756	0.12066

Design	Iteration	D-Efficiency	D-Error
95	0	3.90195	0.25628
	1	8.35069	0.11975
	2	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
96	0	5.88528	0.16992
	1	8.24359	0.12131
	2	8.24359	0.12131

The SAS System

Design	Iteration	D-Efficiency	D-Error
97	0	4.87759	0.20502
	1	8.30579	0.12040
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
98	0	3.89023	0.25705
	1	8.23187	0.12148
	2	8.35069	0.11975
	3	8.35069	0.11975

Design	Iteration	D-Efficiency	D-Error
99	0	3.73719	0.26758
	1	8.30579	0.12040
	2	8.31485	0.12027

Design	Iteration	D-Efficiency	D-Error
100	0	3.68744	0.27119
	1	8.20345	0.12190
	2	8.38593	0.11925
	3	8.38593	0.11925

The SAS System

Final Results

Design	28
Choice Sets	12
Alternatives	2
Parameters	5
Maximum Parameters	12
D-Efficiency	8.3859
Relative D-Eff	69.8827
D-Error	0.1192
1 / Choice Sets	0.0833

The SAS System

n	Variable Name	Label	Variance	DF	Standard Error
1	x11	x1 1	0.11111	1	0.33333
2	x12	x1 2	0.11111	1	0.33333
3	x21	x2 1	0.12500	1	0.35355
4	x22	x2 2	0.12500	1	0.35355
5	x23	x2 3	0.12500	1	0.35355
				5	

The SAS System

Set	Design	Efficiency	Index	Prob	n	x1	x2	_f1	_f2
1	28	8.38593	2	0.5	649	1	2	1	1
	28	8.38593	7	0.5	650	2	3	1	1
2	28	8.38593	5	0.5	651	2	1	1	1
	28	8.38593	4	0.5	652	1	4	1	1
3	28	8.38593	12	0.5	653	3	4	1	1
	28	8.38593	2	0.5	654	1	2	1	1
4	28	8.38593	11	0.5	655	3	3	1	1
	28	8.38593	1	0.5	656	1	1	1	1
5	28	8.38593	8	0.5	657	2	4	1	1
	28	8.38593	11	0.5	658	3	3	1	1
6	28	8.38593	6	0.5	659	2	2	1	1
	28	8.38593	3	0.5	660	1	3	1	1
7	28	8.38593	5	0.5	661	2	1	1	1
	28	8.38593	4	0.5	662	1	4	1	1
8	28	8.38593	9	0.5	663	3	1	1	1
	28	8.38593	7	0.5	664	2	3	1	1
9	28	8.38593	8	0.5	665	2	4	1	1
	28	8.38593	10	0.5	666	3	2	1	1
10	28	8.38593	3	0.5	667	1	3	1	1
	28	8.38593	12	0.5	668	3	4	1	1
11	28	8.38593	1	0.5	669	1	1	1	1
	28	8.38593	10	0.5	670	3	2	1	1

Set	Design	Efficiency	Index	Prob	n	x1	x2	_f1	_f2

12	28	8.38593	6	0.5	671	2	2	1	1
	28	8.38593	9	0.5	672	3	1	1	1

The SAS System
Canonical Correlations Between the Factors
WARNING: There are Duplicate Profiles in This Design
There are 6 Canonical Correlations Greater Than 0.316
C - Constant Factor

	Block	Alt1_x1	Alt1_x2	Alt2_x1	Alt2_x2
Block	C	C	C	C	C
Alt1_x1	C	1	0.47	0.52	0.39
Alt1_x2	C	0.47	1	0.43	0.70
Alt2_x1	C	0.52	0.43	1	0.63
Alt2_x2	C	0.39	0.70	0.63	1

The SAS System
Canonical Correlations > 0.316 Between the Factors
WARNING: There are Duplicate Profiles in This Design
There are 6 Canonical Correlations Greater Than 0.316

		r	r Square
Alt1_x2	Alt2_x2	0.70	0.49
Alt2_x1	Alt2_x2	0.63	0.40
Alt1_x1	Alt2_x1	0.52	0.27
Alt1_x1	Alt1_x2	0.47	0.22
Alt1_x2	Alt2_x1	0.43	0.18
Alt1_x1	Alt2_x2	0.39	0.15

The SAS System
Summary of Frequencies
WARNING: There are Duplicate Profiles in This Design
There are 6 Canonical Correlations Greater Than 0.316
*** - Indicates Unequal Frequencies**

		Frequencies
	Block	12
*	Alt1_x1	3 6 3
*	Alt1_x2	4 3 2 3
*	Alt2_x1	5 2 5
*	Alt2_x2	2 3 4 3
*	Block Alt1_x1	3 6 3
*	Block Alt1_x2	4 3 2 3
*	Block Alt2_x1	5 2 5
*	Block Alt2_x2	2 3 4 3
*	Alt1_x1 Alt1_x2	1 1 1 0 2 2 0 2 1 0 1 1
*	Alt1_x1 Alt2_x1	0 1 2 3 0 3 2 1 0
*	Alt1_x1 Alt2_x2	0 1 1 1 1 1 2 2 1 1 1 0
*	Alt1_x2 Alt2_x1	2 1 1 1 1 1 1 0 1 1 0 2
*	Alt1_x2 Alt2_x2	0 1 1 2 1 0 2 0 1 0 0 1 0 2 1 0
*	Alt2_x1 Alt2_x2	1 1 1 2 0 0 2 0 1 2 1 1
*	N-Way	1 1 1 2 1 1 1 1 1 1 1

The SAS System

Block	Set	Alt	x1	x2
0	1	1	1	2
		2	2	3

Block	Set	Alt	x1	x2
0	2	1	2	1
		2	1	4

Block	Set	Alt	x1	x2
0	3	1	3	4
		2	1	2

Block	Set	Alt	x1	x2
0	4	1	3	3
		2	1	1

Block	Set	Alt	x1	x2
0	5	1	2	4
		2	3	3

Block	Set	Alt	x1	x2
0	6	1	2	2
		2	1	3

Block	Set	Alt	x1	x2
0	7	1	2	1
		2	1	4

Block	Set	Alt	x1	x2
0	8	1	3	1
		2	2	3

Block	Set	Alt	x1	x2
0	9	1	2	4
		2	3	2

Block	Set	Alt	x1	x2
0	10	1	1	3
		2	3	4

Block	Set	Alt	x1	x2
0	11	1	1	1
		2	3	2

Block	Set	Alt	x1	x2

0	12	1	2	2
		2	3	1