Accepted to the 8th European Conference on Social Media, Cyprus, 01.07.2021-02.07.2021:
https://www.academic-conferences.org/conferences/ecsm/

Micro-targeting and non-profit marketing: Loss of serendipity or effective strategy?

Bernardi, Chiara Livia and Mendieta, Carlos
University of Stirling, Stirling, Scotland
SA Consulting, London, England

Chiara.bernardi@stir.ac.uk
Mosca.carlos@protonmail.com

Abstract

This paper presents a novel understanding of programmatic advertising and micro-targeting in the context of non-profit and voluntary sector marketing. It argues that, while these types of automated tactics are met with resistance in current research, they can aid effective non-profit marketing strategy. The critiques levelled at these tactics are twofold: programmatic advertising causes loss of organic discovery of information (or loss of serendipity), and programmatic ads delivered to specific target audiences can be used to spread fake news and influence decision-making. The Cambridge Analytica scandal is perhaps the best example of how these tactics can be used unethically to manipulate behaviour. The paper critically engages with these critiques and argues that, when used effectively, programmatic advertising and micro-targeting can drive more effective results and advance non-profit and voluntary-sector marketing. Building upon human information behaviour, the paper produces a model to unpack the logics behind these strategies and identify best practices for use in non-profit marketing. The model is tested by distributing a digital serious game and an evaluative questionnaire, which has been designed in collaboration with multiple third-sector stakeholders to raise awareness about economic abuse and inform about available support in Scotland. The results demonstrate that the model accurately and effectively reflects users' behaviours when exposed to programmatically delivered messages. Given these outcomes, the paper proposes that programmatic advertising and micro-targeting offer new opportunities for the third sector. This is not to mean that concerns do not exist; rather, to maximise marketing efforts within a third sector and ethically focused context, a strong understanding of content and the algorithmic logics of programmatic distribution is needed. This paper aims to contribute new perspectives on programmatic advertising and micro-targeting and enrich literature and theoretical corpus on these topics in the context of non-profit and institutional marketing.
.

Keywords: programmatic advertising, micro-targeting, serendipitous discovery of information, digital serious games, social media, information encountering.

Introduction

Digital media, analytics (Marchionini, 2006) and analytics-driven marketing intelligence (Krishnan & Rogers, 2015; Yun et al., 2019) are becoming central in commercial marketing practice and research. Programmatic advertising and micro-targeting are commonly used tactics that maximise 'automation in buying and selling of media' (Rogers, 2017, np), intending to improve advertisers' performance. Originally thought to increase the efficiency of remnant inventory after a campaign, programmatic advertising has rapidly emerged as one of the most remunerative, though complex, digital advertising techniques (Rogers, 2017). Along with other aspects of digital marketing, programmatic advertising is one of the by-products of artificial intelligence (AI) applications (Pearson, 2019). Advertisers can gain an in-depth understanding of their customers and deliver relevant messages or information to them by using complex machine learning algorithms that combine diverse types of data and data sources. Likewise, customers are delivered information and messages that they are interested in and can potentially benefit from (Jabbar et al., 2020, Pearson, 2019, Wang et al., 2017). This is possible because of advanced statistical models that cluster digital media users based on their interests, behaviours, and attitudes, allowing for micro-targeting (ChoiJong et al., 2008; ICFNext, 2018; Lawrence, 2020; Summers et al., 2016; Tyagi et al., 2020, as cited in Voth Schrag & Ravi, 2020; Yang et al., 2016). This phenomenon is growing exponentially with the use of intelligent systems such as those developed by giants like *Amazon Demand-side Platform* (DSP), *Facebook* and *Google* (Amazon, 2020). Recommended searches, programmatic adverts and re-marketing techniques (which occur seamlessly across platforms) enable users to encounter information that is potentially interesting to them but is not directly linked to a need (Bode et al., 2015; Ramesh et al., 2017; Saleem et al., 2019). These developments have merged entertainment and real-time data gathering and interpretation, resulting in a balance between intelligence (data and users' information from previous searches and online manifest activities) and creativity (rich content). This combination assists marketers in delivering effective strategies. However, such advances also raise the question of whether users will still 'happen' to come across an unrelated piece of information (an ad or a post) on popular social media platforms and learn something new. These concerns have been surfaced in marketing studies, communication studies and human information behaviour. In their critique of the increased presence of AI in marketing, White and Samuel (2019) maintain that since advertising 'can lead to viewers being repeatedly exposed to the same, or similar, adverts' (p. 163), programmatic advertising has allowed advertisers to deliver relevant (never repetitive) content. Furthermore, they argue that the need to produce interesting content leads to a loss of serendipity, which is usually understood as the act of 'stumbling upon' sources while looking for something else or undertaking an unrelated task (Erdelez & Makri, 2020). Serendipity is a concept rooted in human information behaviour (HIB), and one of its sub-disciplines, library information studies (LIS). Serendipity is typically defined as a 'eureka moment' that occurs whether people are actively looking for information (active information seeking) or not (passive information seeking) (De Keyzer et al., 2015; Erdelez, 1997; McCay-Peet & Toms, 2015).

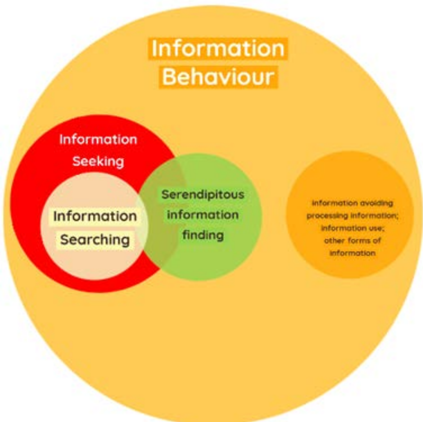


Figure 1. Serendipitous discovery of information (adapted from Agarwal, 2015)

Unlike more traditional forms of advertising (newspaper ads or online formats), programmatic ads tend to be delivered as 'native' content or as newsfeed and sidebar posts and generate the results advertisers require (White & Samuel, 2019). Consequently, serendipitous discovery is lost. Additionally, the Cambridge Analytica scandal raised serious concerns over the exploitation of personal data, and this, compounded with other data gathering and personal information scandals, has only reflected negatively on programmatic advertising, resulting in scant academic research on the subject (Borgesius et al., 2018; Heawood, 2018; Wang et al., 2017). This paper will review and overcome these criticisms by identifying how programmatic advertising can benefit non-profit and voluntary sector marketing. It accomplishes this by combining existing HIB research and apply it to digital media contexts to create a working model for understanding the real contributions of programmatic advertising and micro-targeting. The paper is organised into three parts. The first section proposes a model to address critiques of programmatic advertising: (a) loss of serendipity and (b) perilous and unethical micro-targeting. The second part describes the methodology followed to test the model. The model is evaluated with the programmatic distribution of the digital serious game *Help Mandy!*, which was created with the input of Scottish organisations and advocates to raise awareness about economic abuse in Scotland. The distribution was undertaken through *Facebook Ad Manager*, and A/B testing was done to identify how people interact with the ads and determine any noticeable algorithmic behaviours (e.g. any emerging algorithmic biases that must be considered for successful campaigns). The third segment discusses the findings and what can be learned from this model. This case study is useful for two main reasons. Firstly, the game's distribution was not linked to any organisations' activities, but rather was the outcome of coordination between multiple stakeholders in academia and the third sector. Secondly, the campaign aimed to understand how to best employ programmatic marketing strategies to raise awareness about economic abuse and increase the visibility of the organisations that offer support in Scotland.

Human information behaviour informs marketing strategy.

Digital media analytics (Marchionini, 2006) and analytics-driven marketing intelligence (Krishnan & Rogers, 2015; Yun et al., 2019) are becoming central in the delivery of behavioural and targeted messages. Programmatic advertising is based on the principle that users are delivered (or served) potentially appealing ads and are led to promptly discover new knowledge (e.g. a recommended book, a potential holiday destination or a new restaurant within a specific area). These developments in marketing strategy and advertising pose important questions about how information is found, seen and accessed.

Disciplines such as Human Information Behaviour (HIB) and fields such as library information studies (LIS) see data and information discovery as a central process of human experience. As a result, these disciplines enrich marketing strategy and research and are effective in creating models and protocols to embed programmatic advertising in non-profit and voluntary sector marketing. As discussed, there are multiple criticisms of programmatic advertising. The first important critique is that algorithms decide what people see and discover and where they are exposed to information, based on targeting decisions made on behalf of advertisers by programmatic platforms. Consumers, therefore, lose their right to discover things serendipitously. However, they are also seen as recipients of information that is thrust upon them. In this regard, users absorb what is presented to them and, as a result, seek out programmatically delivered information. The second criticism focuses on the notion that programmatic advertising, through micro-targeting, can potentially be used to deliver inaccurate information or expose users to harmful messages. This critique resonates with growing fears that programmatic mechanisms are employed to exploit and influence opinion (Linvill & Warren, 2020). Nonetheless, it is safe to assume that non-profit and voluntary sector marketing follow the ethical guidelines established by programmatic platforms for the third sector.

Both critiques focus on loss, whether it is a loss of serendipity, privacy and ethical handling of users' data or (perhaps most importantly) the potential loss of independent decision-making (Pearson, 2019; White & Samuel, 2019). However, such a loss does not account for the fact that once information is found, a process is set in motion. Such a process is based on the negotiation between the user and the advertisement. Although programmatic advertising may aid the non-agentic and accidental discovery of information, there is no direct or causal relationship between seeing a programmatically delivered ad and taking an action as a result. Serendipity should be considered as a *process,* rather than a *moment.* This process is particularly interesting and has so far received no attention in programmatic advertising and digital marketing.

Erdelez and Makri (2020) prefer to use the term information encountering (IE) to describe such a process, considering serendipity as too limited and fixed in time. Established in empirical research, IE can be defined as an unexpected discovery of useful, or at the very least interesting, information. Unlike serendipity, IE recognises that information can be of different types (digital or physical) and formats (visual or textual, people or places). IE further posits that once information is discovered an evaluative process is set in motion. Such a process 'can be disrupted at any point if the encounterer (the user in case of programmatic advertising) does not consider the encountered information (thus the ad) interesting, or potentially useful enough to drive the process forward' (Erdelez & Makri, 2020, p. 15). Therefore, the encounterer is not passively exposed, and the encountered information is not passively absorbed. Instead, they engage in various negotiation processes to discern whether the information is worth having immediately, should be stored 'for future use', or is uninteresting and consequently 'brushed aside and lost' (McBirnie, 2008, p. 608).

From a non-profit marketing standpoint, it is important to consider that exposure may pique interest, improve recall or even gain recognition, but it does not guarantee engagement, notice or action. Information can be encountered when a user is searching for other (potentially unrelated) information or simply browsing, which is intended as both the act of spending time online or on social media and a 'form of semi-directed or semi-structured information-seeking' that happens before the user initiates the IE process (Ellis, 1989 as cited in Erdelez, 1997, p. 413; Jiang, Liu & Chi, 2015).

A programmatic advertising model of information encountering

IE represents a highly useful theoretical and methodological framework to understand and unpack the complexity of programmatic advertising and micro-targeting. It proposes a valuable starting point for building a model that identifies how programmatic advertising and micro-targeting can contribute to non-profit marketing. This study's proposed model is based on Erdelez and Makri's (2020) interpretation of IE. However, it is further enhanced by a level of complexity and depth that considers not only actions such as recall and recognition, but also elements such as content (e.g., vertical ads or stories) for the programmatic ads and its role in guiding the user journey from the programmatic ad to the game. In the suggested model, programmatic advertising is recognised as a potential interrupter of the organic flow of browsing and searching online, but it is also seen as a unique opportunity to initiate a dialogue with users who may not otherwise engage with a certain type of information (Bridger, 2016; He et al., 2015; Panetta, 2019; Saleem et al., 2019; Wang et al., 2017). Further building on Erdelez and Makri (2020), our model also consists of three stages (or blocks): pre-encounter, information encounter and post-encounter (Fig.1). However, the proposed steps are non-linear and foresee dynamic movement between the stages. Such non-linearity takes into consideration marketing-specific elements such as the effectiveness of the content, the encounterer's interest and the characteristics of the ad and the platform.

Pre-encounter tasks: At this stage, it is recognised that users both passively and actively encounter information. Ads can be seen when spending time skimming through social media feeds, browsing through social media platforms, or engaging in direct searches on search engines. Therefore, while programmatic advertising can potentially reduce serendipity, it does not necessarily lead to direct action (e.g. attentively noticing or clicking ads) unless the user does not value what it offers. From the perspective of non-profit marketing, programmatic advertising could allow a message to be distributed across multiple and diverse audiences, enabling it to be noticed by a potentially large number of people. However, this does not count as a 'eureka moment', which is typically associated with serendipitous discovery (Agarwal, 2015). Rather, it is an instance when new information is encountered and potentially noticed (though not necessarily further investigated).

Information encountering: Once the information is encountered, several processes are set in motion. Adapted from Erdelez and Makran's (2020) work, our model recognises that once an ad has been served programmatically and encountered by the user, multiple scenarios arise. The user may notice the advert but decide to either ignore or pay closer attention to it. For the advertisement to be noticed and considered, it must offer information that is of value (Foster & Ford, 2003). Otherwise, the user may decide to stop viewing or considering the information and return to any pre-encounter activity. Although content can be delivered programmatically, the user cannot be viewed as a passive recipient of data. Hence, a careful evaluation of what users consider valuable is necessary. From a commercial marketing perspective, users may assign a value to advertisers based on multiple factors (e.g. content or call to actions). For non-profit marketing, the value becomes more complex because the objectives of non-profit campaigns do not lead to users' immediate satisfaction (e.g. donations, fundraising or awareness may not be immediately useful or of value) (De Keyzer et al., 2015). If the encountered information is deemed valuable, the user may choose to engage with it further, abandon it and return to their pre-encountering tasks or stop searching or browsing in the digital space. As Erdelez and Makri (2020) noticed, the IE process can be stopped or interrupted at any point, and several factors may intervene. These can be user-related (e.g. mood), information-related (e.g. data), task-related (actions that users must do as a response to the information), and environment-related (the overall environment). However, in our model, other factors may intervene, all of which are very specific to digital and social media communication. These include the content and narrative proposed, formats chosen to present the information, platforms, information design (e.g. the easy integration between the platform where the ad is served and the landing page where more information and explanation can be found) and action that must be taken (e.g. the call to action).

Post-encounter tasks: If all the conditions in the information encountering stage work harmoniously, users can move to the final stage, which entails taking actions. These may either be specifically responsive to the ad (e.g. do as the ad proposes) or not directly responsive to the ad but still valuable for the advertiser (e.g. increased recognition or recall).

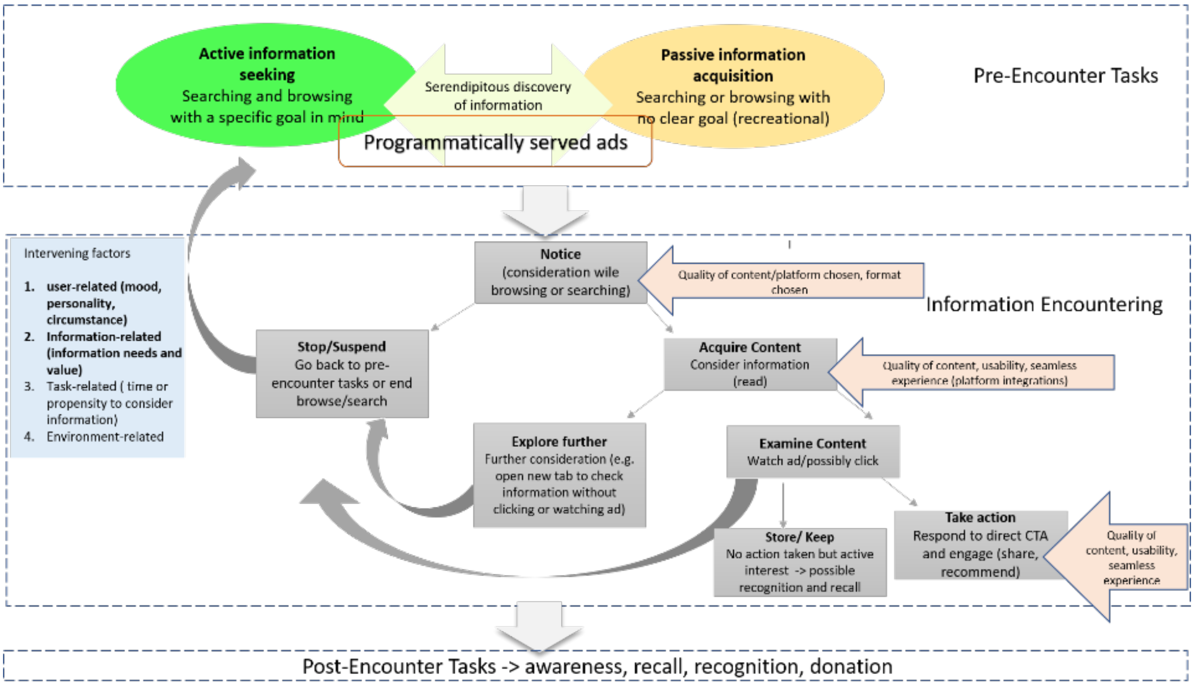


Figure 2. IE and Programmatic Advertising model (enriched and adapted from Erdelez and Makri, 2020)

Research design

This model was developed based on Erdelez and Makri's (2020) work to find the best ways to partner with multiple Scottish organisations and charities that offer financial support and advice to victims and survivors of domestic violence, with a special focus on viable aid for victims and survivors of economic abuse. Given the general lack of coordinated communication strategies, the decision was made to create a digital serious game and distribute it programmatically.

The objective of the game was twofold: (a) to raise awareness about economic abuse and its multiple manifestations to a large audience and (b) to inform players about the support available for victims, survivors and anyone interested (i.e. financial literacy programmes, financial support in case of debt and savings plans offered by credit unions). The paper does not engage with the rationale, structure, and narrative of the game, but focuses on the game's distribution and results. The distribution of the game considered multiple factors. It required a clear content and targeting plan that included sufficient material to generate a set of different ads to be distributed programmatically over a given period across multiple platforms to various types of audiences with unknown behavioural or attitudinal preferences (Tab.1). The dissemination was also perceived as a critical investigative step in further defining and understanding how different audiences engage with sensitive content to refine behavioural targeting and improve strategy.

Type of Ad (a)	Time (t)	Platform (p)	Audience (c)
Factual (focus on economic abuse); Ludic (focus on a game about economic abuse)	The budget allocated for one week: GBP 50	**Instagram,** TikTok, Snapchat, **Messenger (FB)**, **WhatsApp**	18–24
		Instagram, TikTok, **WhatsApp**	25–34
		Instagram, TikTok, **WhatsApp, Facebook (declining)**	35–44
		Instagram, Facebook, (growing TikTok), **WhatsApp**	45+

Table 1. Ad by platform by the audience. 'Usage penetration rate of social networks among active internet users in the United Kingdom (UK) as of Q3 2019' (Statista, 2020).

To minimise the number of ads produced across platforms, *Facebook for Business* was chosen. Two key factors influenced this decision:

1. *Instagram* and *Facebook* are widely used in Scotland (Statista, 2020), with Instagram being more popular among younger target audiences (18–24 and 25–30) and Facebook being more common with the older demographic (45+).
2. The advertising platform allows the uploading of several ads while keeping the technical specificities for the ads to a minimum.

Unlike *Twitter* or *Google*, Facebook for Business helps create gifs or short videos of images (carousel) from within the platform, keeping content production costs contained (Tab.2).

Platform (p)	Advertised Network	Target Audience 18–45+	
Facebook for Business	Facebook ads	Edinburgh: 20km	Savings, National Network to end domestic violence, Motherhood, Consumer debt, Money, Fatherhood, Personal finance, Financial plan, Home equity loan, Savings account, Parenting, Passive income, Home equity line of credit, Childcare, Credit cards, Savings bank or refinancing, Parents, College (all), College (in-market, all), Retirement, Retirement plans, Retirement (all)
	Facebook featured ads	Dundee: 40km	
	Instagram ads	Inverness: 40km	
	Instagram stories	Aberdeen: 40km	
	Messenger	Glasgow: 20km	

Table 1. Geographic and behaviour/attitude targeting

Due to the lack of insights about which type of target audiences will be more interested in learning about economic abuse and engaging in a related educational game, a total of six different ads in the form of posts were crafted and clustered into two categories: factual ads and ludic ads. Each cluster involved a graphic interchange format (GIF), a carousel (a photo collage story that a user can tap on the screen, which brings about different messages) and a still image. Three factual ads stressed the seriousness of economic abuse in Scotland and invited the audience to play a game so they can learn more about available resources.

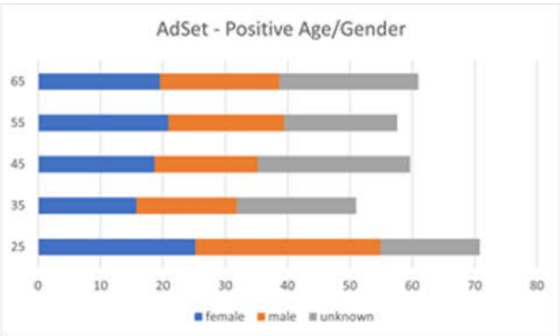
As they play the game, the user is prompted to 'Learn More', or what is known in marketing as a 'call to action'. Three ludic ads highlighted the gaming aspect and invited the users to a challenge. Statistics on bankruptcy and victims of economic exploitation in Scotland in 2019 were used so the audience can test their financial literacy skills and ability to remain economically independent. Even with the ludic ads, the user is directed to the game *Help Mandy!* through the call to action, 'Learn More'. One ad from each cluster was chosen for A/B testing to understand how to best distribute a serious game about economic abuse in Scotland. The authors anticipated that ludic ads may attract more interest than factual ads. Thus, to avoid skewed results, a GIF was employed for the factual ad and a plain picture was selected for the ludic one.

Findings

The ads were run programmatically for one week from 1 July 2020 to 8 July 2020. The allocated budget was minimal (GBP 50) given the experimental nature of our model. The metrics recorded by *Facebook Ads Manager* include impressions, frequency and results (clicks). *Impressions* is an exact metric of how many times an ad is delivered, while *frequency* is an estimated metric calculated by dividing impressions by results.

Pre-encountering tasks: In line with the literature on programmatic marketing techniques, it was anticipated that delivered impressions would influence the serendipitous discovery of the digital serious game and that the ads would have the same probability of being distributed to the selected audiences over the campaign's duration.

The results indicated that the factual ad, which took a negative approach to the game, was more intensely viewed by younger and female audiences (25–35) than the authors had expected. In contrast, older audiences (55 onward) preferred a more positive approach to the message (Fig.2).



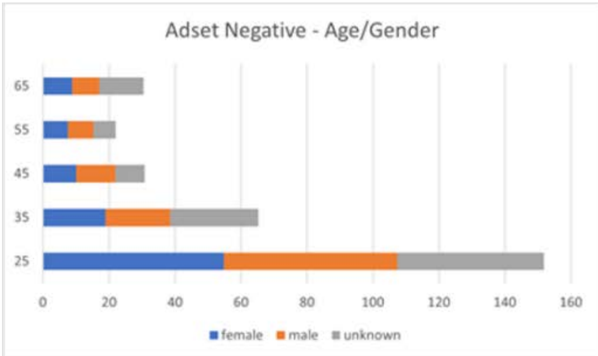


Figure 3. Frequency

		Gender		
Ad set name	**Age**	**female**	**male**	**unknown**
Creative 1- Emotional positive	25	21.25%	22.36%	11.05%
	35	11.95%	13.44%	23.26%
	45	17.77%	16.31%	18.02%
	55	25.66%	24.02%	18.6%
	65	23.38%	23.86%	29.07%
Creative 2 - Emotional Negative	25	53.36%	48.68%	27.33%
	35	17.66%	20.94%	25.58%
	45	10.47%	11.8%	12.21%
	55	8.06%	8.24%	6.4%
	65	10.45%	10.34%	28.49%

Figure 4. Delivered impressions

However, a closer evaluation of the delivered impressions (Fig.3) revealed that younger audiences are more likely to receive factual ads (nomenclature clarification: emotional negative), while older audiences were more likely to be delivered positive ads (nomenclature clarification: emotional positive) (χ^2 104.26578527225, $p < 0.01$, dof=8, Cohen w=.37). These results are significant and warrant further investigation over a longer time frame and with a greater budget. Despite these limitations, the findings evidenced that certain messages should also be communicated in relation to potential algorithmic biases. To the best of the authors' knowledge, this study is the first to identify and report on actual biases of algorithms.

Information encountering and post-encountering activities: The A/B testing confirmed the multiple steps and evaluations users go through when engaging with programmatically served ads. The ads were disseminated over 18,000 times in the space of one week. However, these delivered impressions did not automatically lead to a successful campaign, confirming that IE is a process and that programmatic ads and micro-targeting do not necessarily result in immediate consideration and investigation of the data encountered regardless of the content.
Rather, users engaged in multiple steps and abandoned the process at various points. The campaign generated 59 clicks (action). Of these, a total of 40 people participated in the post-encountering task, which in this case included playing the game and answering a post-game questionnaire. Therefore, there was a major loss of potential user engagement due to multiple factors. Conversely, there was no significant difference between formats, with the ludic ads' still image producing 33 clicks (emotional positive) against the factual ads' gif generating 26 clicks (emotional negative). However, it was not possible to identify which users clicked on the ad and continued to play the game and answer the questionnaire. Nevertheless, the results of the questionnaire indicated the game was useful and offered positive feedback of the advertising propositions, highlighting that the players' understanding of the issue and awareness of available support had increased after playing the game. The inclusion of the organisations' sites within the game was one of the main critiques expressed by users who responded to the questionnaire (n=12), denoting the important role of seamless integration.

Limitations and future research

The experiment brought to light interesting elements. However, we recognise that the campaign was executed in an extremely short timeframe with a very limited budget. Therefore, a longer and better-funded campaign will be undertaken to further validate the results and refine the proposed model. We also acknowledge the need to make better use of pixels to better understand how users interact with the ads and to integrate design theories to further assess the validity of our model. The model we proposed focuses on the impact of programmatic advertising on the discovery of and engagement with information about economic abuse and problematises easy considerations about its effects on users' attitudes and behaviours. Moving forward, more attention and a better-refined conceptualisation of content in the model is needed to improve current research on the relationship between pre-encounter task, information encountering stage and post-encounter tasks. More programmatically run ads will allow further development of and strengthen the content's impact on the model. We also note that the model concentrated on the transition between pre-encounter tasks and the information encountering stage to identify the possibilities that programmatic advertising offers to non-profit marketing. More research is therefore needed to assess how information encountering leads to post-encountering tasks. When combined, this information will contribute to the design and implementation of effective programmatic marketing strategies for non-profit purposes.

Conclusion

This paper has demonstrated that programmatic advertising and micro-targeting can offer unique opportunities to the third sector. However, for these opportunities to flourish, both programmatic advertising and micro-targeting must be understood as part of a far more complex process that requires planning and attentive behavioural simulations. The proposed model can be used to investigate how to create content and identify a journey for users to engage in, consider, and evaluate, with the ultimate aim of prompting them to take certain actions. This is especially useful for non-profit and voluntary-sector marketing given the uniqueness of their propositions, the majority of which are not products or services, but actions that require users to engage, share and donate. The paper aspires to contribute new insights into programmatic advertising and micro-targeting, as well as enrich the literature in the field of non-profit and institutional marketing.

References

Agarwal, N. K. (2015). Towards a definition of serendipity in information behaviour. *Information Research, 20*(3), 1-16. https://files.eric.ed.gov/fulltext/EJ1077837.pdf
Amazon (2020). *AMAZON DSP.* Amazon Advertising. https://advertising.amazon.co.uk/en-gb/products/amazon-dsp
Bode, L. et al. (2015). Candidate networks, citizen clusters and political expression: Strategic hashtag use in the 2010 midterms. *Annals of the American Academy of Political and Social Science, 659*(1), 149–165. https://doi.org/10.1177/0002716214563923
Borgesius, F. J. Z. et al. (2018). Online political microtargeting: Promises and threats for democracy. *Utrecht Law Review, 14*(1), 82–96. https://doi.org/10.18352/ulr.420
Bridger, D. (2016). Decoding the irrational consumer: How to commission, run and generate insights from neuromarketing research (1st ed.). Kogan Page.
Campbell, J. (2019). *How to use Facebook ads for charity and non-profits*. The Balance Small Business. https://www.thebalancesmb.com/how-to-create-fab-but-cheap-nonprofit-ads-for-facebook-2502544
ChoiJong, A. et al. (2008). Need for cognitive closure and information search strategy. *Psychology and Marketing, 25*(11), 1027–1042.
Choo, C. W., & Auster, E. (1993). Environmental scanning: Acquisition and use of information by managers. *Annual Review of Information Science and Technology, 28*(n/a), 279–314.
Cooney, R. (2020, Month Day). TikTok launches in-app donations feature. *Third Sector*. https://www.thirdsector.co.uk/tiktok-launches-in-app-donations-feature/fundraising/article/1681552
De Keyzer, F., Dens, N., & De Pelsmacker, P. (2015). Is this for me? How consumers respond to personalised advertising on social network sites. *Journal of Interactive Advertising, 15*(2), 124–134. https://doi.org/10.1080/15252019.2015.1082450
Erdelez, S. (1997). Information encountering: A conceptual framework for accidental information discovery. In ISIC '96 Proceedings of an international conference on Information seeking in context. Tampere, Finland, Taylor Graham Publishing, 412–421.
Erdelez, S., & Makri, S. (2020). Information encountering re-encountered: A conceptual re-examination of serendipity in the context of information acquisition. *Journal of Documentation, 76*(3), 731–751. https://doi.org/10.1108/JD-08-2019-0151
Erdelez, S., & Rioux, K. (2000). Sharing information encountered for others on the Web. *The New Review of Information Behaviour Research, 1*(January), 219–233.
He, W. et al. (2015) A novel social media competitive analytics framework with sentiment benchmarks. *Information and Management, 52*(7), 801–812. https://doi.org/10.1016/j.im.2015.04.006
Heawood, J. (2018). Pseudo-public political speech: Democratic implications of the Cambridge Analytica scandal. *Information Polity, 23*(4), 429–434. https://doi.org/10.3233/IP-180009
ICFNext. (2018). (Date of last update). *Humanising Loyalty*. ICF.
Jabbar, A., Akhtar, P., & Dani, S. (2020). Real-time big data processing for instantaneous marketing decisions: A problematisation approach. *Industrial Marketing Management, 90*(November 2018), 558–569. https://doi.org/10.1016/j.indmarman.2019.09.001
Jiang, T., Liu, F., & Chi, Y. (2015). Online information encountering: Modelling the process and influencing factors. *Journal of Documentation, 71*(6), 1135–1157. https://doi.org/10.1108/JD-07-2014-0100
Krishnan, K., & Rogers, S. P. (2015). *Social data analytics: Collaboration for the enterprise*. Morgan Kaufmann Series On Business Intelligence.
Lawrence, C. (2020). *Facebook lookalike audience changes: What marketers need to know*. Social Media Examiner. https://www.socialmediaexaminer.com/facebook-lookalike-audience-changes-what-marketers-need-know/
Linvill, D. L., & Warren, P. L. (2020). Troll factories: Manufacturing specialised disinformation on Twitter. *Political Communication, 37*(4), 447–467. https://doi.org/10.1080/10584609.2020.1718257
Marchionini, G. (2006). From finding to understanding. *Communications of the ACM, 49*(4), 41–46.
Mc Birnie, A. (2008). Seeking serendipity: The paradox of control. *Aslib, 60*(6), 600–618.
McCay-Peet, L., & Toms, E. G. (2015). Investigating serendipity: How it unfolds and what may influence it. *Journal of the Association for Information Science and Technology, 66*(7), 1463–1467. https://doi.org/10.1002/asi

Mutula, S. M. (2020). Active and passive information behaviour of the professoriate: A descriptive comparative pattern analysis.SA Journal of Information Management, 1–12. https://doi.org/10.4102/sajim.v22i1.116
Panetta, K. (2019). *How to create an effective customer journey map*. Gartner. https://www.gartner.com/en/marketing/insights/articles/how-to-create-an-effective-customer-Journey-map
Pearson, A. (2019). Personalisation the artificial intelligence way. *Journal of Digital and Social Media Marketing, 7*(3), 245–269.
Ramesh, S., Delen, D., & Turban, E. (2017). Business intelligence, analytics and data science. Pearson.
Rogers, C. (2017). *What is programmatic advertising? A beginner's guide*. Marketing Week. https://www.marketingweek.com/programmatic-advertising/
Saleem, H. et al. (2019). Strategic data-driven approach to improve conversion rates and sales performance of e-commerce websites. *International Journal of Scientific & Engineering Research, 10*(4), 588–593.
Samuel, A. et al. (2020). Programmatic advertising: An exegesis of consumer concerns. *Computers in Human Behaviour, 116*(online), 106657. https://doi.org/10.1016/j.chb.2020.106657
Summers, C. A., Smith, R. W., & Reczek, R. W. (2016). An audience of one: Behaviourally targeted ads as implied social labels. *Journal of Consumer Research, 43*(1), 156–178. https://doi.org/10.1093/jcr/ucw012
Thompson, D. (2018, February, 7). Where did all the advertising jobs go? *The Atlantic.* https://www.theatlantic.com/business/archive/2018/02/advertising-jobs-programmatic-tech/552629/
Voth Schrag, R. J., & Ravi, K. (2020). Measurement of economic abuse among women not seeking social or support services and dwelling in the community. *Violence & Victims, 35*(1), 3–19.
Wang, J., Zhang, W., & Yuan, S. (2017). Display advertising with real-time bidding (RTB) and behavioural targeting. *Foundations and Trends in Information Retrieval, 11*(4–5), 297–435. https://doi.org/10.1561/1500000049
Wang, P., Gao, M., & Sinnott, R. O. (2017). Enhanced gender identification through social media analytics on the cloud. In IEEE 18th International Conference on High Performance Computing and Communications, 14th IEEE International Conference on Smart City and 2nd IEEE International Conference on Data Science and Systems, (pp. 1426–1433). IEEE https://doi.org/10.1109/HPCC-SmartCity-DSS.2016.0203
White, G. R. T., & Samuel, A. (2019). Programmatic advertising: Forewarning and avoiding hype-cycle failure. *Technological Forecasting and Social Change, 144*(February), 157–168. https://doi.org/10.1016/j.techfore.2019.03.020
Yang, K. C. et al. (2016). Applying social marketing theory to develop retargeting and social networking advertising website. In Editor Name/s (Ed./Eds.), *IEEE International Conference on Industrial Engineering and Engineering Management* (pp. 1845–1849). Publisher. https://doi.org/10.1109/IEEM.2015.7385967
Yun, J. T. et al. (2019). Computationally analysing social media text for topics: A primer for advertising researchers. *Journal of Interactive Advertising, 47(59)*), 1–13. https://doi.org/10.1080/15252019.2019.1700851