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The Generation Z audience for in-app advertising

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Abstract

Purpose: The audience for in-app mobile advertising is comparable in size and viewing rate to that for TV but divides its attention across a highly fragmented selection of apps, each competing for advertiser revenue. In market, the assumption is that this audience is deeply segmented, allowing individuals to be contextually targeted on the apps that define their interests and needs. But that assumption is not supported by the Laws of Double Jeopardy and Duplication of Viewing which closely predict usage in other mass media. Our purpose is to benchmark in-app audiences against these laws to better understand market structure.

Method: We collected nearly three thousand hours of screen time data from a panel of Generation Z respondents and tested the predictive validity of two models against observed interactions with twenty-three popular apps in six categories over a week.

Findings. Results show that contrary to industry assumptions, this audience for in-app advertising is *not* segmented. Engagement on individual apps and sharing rates between apps and app formats is predicted well.

Originality/Value: Many authors have called for consistency in metrics to compare on and off-line media performance. This study bridges that gap, demonstrating how reach and frequency measures could inform digital scheduling for contextual targeting.

Implications Optimising in-app advertising for short-term activation only limits its potential for brand-building. These findings encourage advertisers to schedule online campaigns for brand reach as well as sales lift, by advancing current understanding of audience behaviour.

Keywords: Duplication of Viewing, Double Jeopardy, Generation Z, in-app advertising, Contextual Targeting.

The Generation Z audience for in-app advertising

Introduction

Do generalised media-planning laws such as Duplication of Viewing (Goodhardt, 1966) and Double Jeopardy (Barwise and Ehrenberg, 1988) adequately describe audience behaviour in the mobile in-app advertising market? The question is prompted by structural changes affecting the ad-tech industry, specifically the consumer shift onto mobile apps (Dogtyev, 2019), and the new privacy-focussed strategies of Apple and Google. As a result, publishers and ad-networks including major platforms, are now promoting contextual rather than behavioural targeting strategies to advertisers (Hao et al, 2017; Schuh, 2020).

Behavioural targeting relies on tracking data. This summarizes an individual user's past website visits and usage, ad exposures and purchasing. Over the past twenty years Data Science has delivered the astonishing capabilities required by the ad-tech industry to understand, employ and optimise this data (Saura, 2020) for immediate clicks, downloads and purchase. Contextual targeting is different. It is supported by *"privacy preserving"* data that captures the *"when and the where"* of an ad impression (Rageiaian and Yoganarasimhan, 2020), so advertisers target an audience based not on where they individually *were*, but on where they collectively *are*. For example, a budget airline might infer that users of a specific travel destination app have some interest in reaching the cities it reviews, and bid to serve ad impressions on it, rather than identifying individual frequent fliers from their own or a third-party list and serving ads as those users browse a range of other, often unrelated, apps.

But the trend from contextual to behavioural targeting carries wide ranging implications, which have attracted some academic attention. For instance, there will be an adjustment to the division of revenues from app-monetisation. Rageiaian and Yoganarasimhan (2020) find that although behavioural targeting is likely to produce far higher click-through rates, ad-network revenues improve with contextual targeting. Thus, they argue, the market will favour consumer interests in preserving privacy. Hao et al (2017) identified the same, and suggested ad-networks and publishers were promoting contextual targeting.

Further, contextual targeting may be more popular with advertising audiences. In a study of Generation Y mobile phone users in India, Bhave et al (2013) examined attitudes towards in-app advertising. They found that many of the attributes of contextual targeting are major determinants of positive attitude, for example, the level of involvement with a particular app and the relevance of its advertising, as well as its privacy attributes such as permission and control. And yet, how effective is contextual targeting for advertisers? At the least, it must deliver a different *quality* of audience. Behavioural targeting identifies such high-propensity users that payment by results (e.g., in PPC or PPD) has long been built-in, so for marketers, the short-term ROI of "intent marketing" is now embedded, though it does little to maintain the lighter propensities of the wider customer base (Fulgoni, 2018; Montague, 2019).

For the time being, advertisers can easily pursue a behaviourally targeted audience inside the walled gardens of big tech Outside, competition for the remaining third of global in-app publisher revenues (Dogtyev (2019) is increasingly based on the fragmentation of audience attention across available apps and the assumption that a brands' target market are concentrated on certain vehicles. Contextually targeted advertising is, so the pitch goes, effective and efficient because it reaches the segmented, engaged audience on specialist apps. An almost ubiquitous use of social media, and the development of Information Science allow analysis of user generated content (Reyes-Menendez et al 2020) to usefully define social groups and networks which contribute to meaningful target audience profiles.

But to what extent do the major platforms, individual apps, or even categories of app, really "own" such an audience? Mass media channels have long advocated contextual targeting (Nelson-Field and Riebe, 2011), although it has been known for at least fifty years that TV and even radio audiences are homogeneous and not segmented (e.g. Agostini, 1961; Barwise and Ehrenberg, 1988; Lees and Wright, 2013). However, that knowledge informs better media planning, particularly in regard to setting audience reach and frequency objectives. The difficulty here is that although traditional planning is defined in this way, the metrics are not consistent across online and offline channels (Binet & Carter, 2018; Fulgoni, 2018), and it is unknown if the normative benchmarks apply to an in-app audience. Thus, our aim is to establish if knowledge of media consumption extends to mobile app usage, since much of it can no longer be behaviourally targeted. We benchmark an audience considered hard-to-reach *outside* mobile - Generation Z - against three laws of media planning.

We find, surprisingly, that this in-app audience is consistent with that for TV (e.g. Barwise & Ehrenberg, 1988; Goodhardt, 1966; Nelson-Field & Riebe, 2011; Taylor *et al*., 2013), but not as described in practice! It is unsegmented, there are no niche apps or category of app with a particularly specialist audience, and the duplicated audience on apps and in app categories is predictable. Thus, we can provide a consistent view of effectiveness between old and new media, highlight several implications for advertisers, and suggest a hidden benefit from contextual targeting – its ability to activate some *future* sales. We proceed as follows. We contrast the current in-app advertising proposition with a review of the laws of media planning to formulate our questions. We then describe the data and analysis, present results and discuss their implications.

Theoretical Context

In-App Advertising

The penetration and usage of smartphones have grown rapidly. An estimated 76% of adults (O'Dea, 2020) spend over three hours per day on average using them (MacKay, 2019). One feature of the user experience is the choice of applications (apps) that can be installed, giving online access to information and an almost endless range of entertainment, social and retail activities directly from the device home screen, without using a browser.

Many apps are free to install and use because they attract revenues which are split between the publishers (platforms such as Facebook or Apple), the developers (e.g. Imangi with Temple Run), and ad-networks that match app-user profiles to serve ad impressions programmatically. For advertisers, mobile apps are an important medium because smartphone users now spend 90% of their device-time on them (Wurmser, 2019). In-app mobile delivers a total audience for advertising that is close to that of TV, which has daily reach of 70% in most countries, and average daily viewing of over three hours (thinkbox, 2020). Advertisers go where the audience is and even well-established global brands now place advertising in mobile apps (Atkins, 2019).

In the ad-tech market, app publishers (like all media owners) and ad-networks compete for a share of a finite audience. Many authors have considered different monetisation regimes in the market between developers, platforms, and ad-networks (Ghose and Han, 2014; Ji, Wang and Gou, 2019; Tang, 2016; Truong *et al,* 2019). The general finding is that advertising suppresses demand for an app but not by very much, so of the three monetisation models; pay to install; freemium; and free with advertising, the last has become widespread. Apps do not support third-party cookies, and therefore outside the major platforms (where an audience signs in and can be tracked) it can only be targeted contextually.

In response, publishers and ad-networks sell in-app audience to advertisers on the promise of user engagement. The argument is that if users can be defined by and are engaged with app content, then congruent advertising is considered effective (e.g. Belanche, Flavián & Pérez-Rueda, 2017). Determinants of attitudinal and behavioural response to in-app advertising have been studied on dimensions including contextual congruity (Rutz *et al,* 2019; Wang and Chou, 2019), trust (Cheung and To, 2017; Tapanainen *et al*., 2020), use and gratification (Logan, 2017), and culture (Sigurdsson *et al.,* 2018). These studies tend to apply persuasive hierarchy models, which specify high exposure weights targeted at a limited audience most prone to buy (Shankar *et al.,* 2016). They suggest on this basis that like behavioural targeting, contextual delivery can achieve immediate advertising response.

How Advertising Works

Overwhelming evidence suggests however that most advertising is a weak rather than a strong force (Barnard and Ehrenberg, 1997; Ehrenberg, 2000; Vakratsas and Ambler, 2000). It reminds rather than persuades, and it reaches and reminds very large numbers of people, and in particular those with a low propensity to buy the brand – that is, it keeps brand memories strong until the next category purchase occasion. Practitioners (e.g. Binet & Carter, 2018; Clemmow, 2012; Feldwick, 2015; King, 2008) accept that advertising outcomes are explained by a low-involvement hierarchy of effects, such as Ehrenberg's (1974) ATR model (Awareness – Trial – Reinforcement). In this sequence, a consumer may already have a slight awareness of a brand in a category they regularly buy, but only after trying it, do they form an attitude or a preference. Brand experience (the sum of all prior brand experiences in memory - purchase, usage, and advertising) is then elaborated by subsequent exposures which accumulate to refresh memory and reinforce repeat purchase (Vakratsas and Ambler, 2000; Zenetti & Klapper, 2016).

Brand experience is considered more important than evaluative attitude in predicting future purchase. Attitudinal responses vary greatly between users and non-users of a particular brand, but not by much between users of competing brands. Advertising can therefore hardly be persuasive (Ehrenberg, 2000). It must work not by changing evaluative attitudes about Brand X ("Oh! Then it must taste better"), but by reminding consumers of what they already know ("ah yes, I like that one too"). In most categories, consumers are experienced and split-loyal, dividing successive choices over Brands X, Y, and occasionally Z. The relative strength of brand experience is thus likely to be the determinant of the order of those choices.

The concept of effective frequency (Ephron, 1995; Krugman, 1972) is important here. Where every exposure costs money, there is great interest in establishing the number of exposures needed to maximise response. If the purpose of advertising is to refresh and remind, then studies indicate that three (Tellis, 1997), two (MacDonald, 1971) or even a single exposure (Gibson, 1996; Taylor *et al,* 2009) are enough. Brand lift advertising efficiency therefore depends on maximising reach to remind the largest affordable audience of what they already know, without wasteful repetition. This is the reverse of behavioural targeting which nudges the already high propensities of a (relatively) small number to activate immediate response.

And yet reach is critical for brands seeking to increase market share. Brands grow by increasing penetration (Dawes, 2016; Sharp, 2010), and need broad reach media to achieve it. Penetration-focussed advertising that reaches a brand's lightest buyers is effective (Binet and Field, 2009) because even though prior brand usage moderates the effects of visual attention on advertising recall, light and non-users show some effects after exposure, particularly to video (Simmons *et al*., 2020). Contextual targeting might deliver this reach, while behavioural targeting would not, by design.

Generation Z

For marketers with share growth objectives, Generation Z is considered a valuable source of new brand buyers. Even though they spend more time than average on mobiles and little time on TV (Dimock, 2019; Priporas *et al,* 2017), they shop for brands, including luxury brands, in the real world (Rahilly *et al*, 2020). Could in-app advertising reach Generation Z broadly enough to deliver brand lift? More importantly for advertisers, could contextual advertising effectively target this segment on specific apps, aligned with specialist interests? We address this next, drawing on three established laws in audience behaviour to develop our research questions.

Targeting

The first benchmark concerns targeting on specific media. Barwise & Ehrenberg (1988) found that particular TV programmes or types of programme are *not* mainly viewed by an identifiable population subgroup (e.g., men, women, fitness enthusiasts) in the way that sometimes occurs with specialised magazines or newspapers. They examined the audience composition for seven categories of TV show (e.g., Light Entertainment, Sport, News) and found it surprisingly similar across all genres. The important variation was in audience size. For advertisers this presents an opportunity to target some duplication in less popular programmes at a lower cost. The general pattern they describe is that TV channels, programme types, and programmes do not win large audiences by appealing to different types of people. Instead, viewers choose to watch a variety of shows and a great deal of television over the course of a week, so that most viewers of one programme (or even one channel) spend far more time on other programmes or channels than they do on that one. Therefore, when considering audience behaviour, reach (the number of viewers a show or channel attracts) is far higher than share of viewing; a large number of people watch even a small show, but it only accounts for a small part of their *total* viewing in that week.

The basis of contextual targeting is that the apps downloaded to an individual's phone say something about their interests, needs and wants, and therefore define discriminating demographic or attitudinal differences. But is app-usage really different from TV viewing, in that one app or category might account for *most* of a user's weekly time online? Games are a case in point perhaps. And for Generation Z, is engagement segmented by gender – for example in the use of fitness or social media apps? Importantly, are such biases large enough to drive managerially significant differences in screen time when contextually targeting?

Apps collect first-party data on an opt-in basis and allow targeting by gender and age, as well as by geo-location. Advertisers can buy a wide range of audience defined by behavioural and location data, but the profiling purchased by the majority is still on age and gender (Neumann *et al*, 2019), therefore, to investigate possible segmentation of the in-app audience, and hence its contextual "targetability" it is initially sufficient to consider gender and age only to:

RQ1. Describe app usage and audience composition across app categories.

Audience engagement and fragmented media

A second regularity reported in the behaviour of the TV audience is the law known as Double Jeopardy. This is a relationship that describes liking and viewing rates for programmes, programme types, and channels when:

> *"...people have to choose between broadly similar items that differ in popularity. The less popular items are not only chosen by fewer people but are also liked somewhat less by those who choose them."*
>
> (Barwise and Ehrenberg, 1988 p. 44)

The result of this statistical selection effect in TV viewing is, for example, that lower-rating programmes systematically have lower audience repeat rates (p.44), and smaller channels attract lower hours per viewer than larger ones (p.72). The pattern replicates in different media (Barwise and Ehrenberg, 1987; Donthu,1994; McDowell & Dick, 2005; McPhee, 1963) and it is rare to find a small audience that so likes a channel or show it views or listens to it unusually heavily; two examples in the US are Spanish language and religious channels.

The Double Jeopardy relationship is summarised mathematically using the formula:

$$w\,(1 - b) \cong \text{ a constant}$$

where w is an average frequency and b a proportion of some known population. Ehrenberg *et al.* (1990) demonstrate its use in predicting repeat-purchase loyalty from penetration in consumer goods, and Graham *et al.* (2017) reports many recent extensions. The evidence is that in most competitive situations w is *not* independent of b.

A specialist audience on every app?

In their description of the audience for television, Barwise and Ehrenberg (1988) highlighted a prediction, prevalent at that time, that the arrival of cable TV would lead to audience fragmentation into small but engaged audiences on specialist channels. Such a targetable audience is normally offered to relevant advertisers at a premium price. But instead, their earlier Double Jeopardy findings were replicated by Collins *et al.* (2003) which specifically examined the impact of channel proliferation, and then again by Nelson-Field and Riebe (2011) which investigated fragmentation effects across TV, radio, and magazines. The Law therefore remains robust across different media and it predicts that a smaller audience is likely to be less, rather than more, engaged with the content.

The app audience is itself highly fragmented, and the offer to relevant advertisers of a specialist and heavy viewing audience on particular apps is once again underpinning the sales pitch by ad-networks and platforms. Hao, Guo and Easley (2017) report, in their analysis of in-app advertising pricing, that platforms/publishers are attempting to increase the value of their advertising revenues by matching the ads displayed in a congruent app with app user characteristics – the definition of contextual targeting.

While congruence between media and advertisement is widely considered a determinant of effectiveness (Moorman, Neijens & Smit, 2013; Rutz *et al,* 2019; Wang and Chou, 2019), and session time affects the likelihood of an impression fully downloading, (Nelson-Field, 2020), without behavioural targeting are certain apps capable of delivering an audience that stays longer? And are some apps inherently *less* able to deliver that engaged audience? The expectation (Barwise & Ehrenberg,1987) is that the most popular apps (i.e. those that deliver the highest views) would also have the longest session times. The Law of Double Jeopardy is a fixed relationship, so audience engagement with any app is empirically testable, hence the second research question:

RQ2. Is user engagement with mobile apps constrained by the Law of Double Jeopardy?

Duplication of Viewing

Of the empirical generalisations in TV scheduling, the Duplication of Viewing Law is perhaps the most practical. It states that the proportion of the audience for programme B that also watches programme A typically varies only in line with the rating of programme A. The overlap is also typically low. For any pair of programmes on different channels and on different days, the duplication of B with A is generally the same as the rating for A (Goodhardt, 1966).

This third benchmark is applied by media planners to optimise spend because it predicts the extent to which any combination of programmes is likely to deliver unique reach and duplicated audience. Sharp, Beal and Collins (2009) have however documented an emerging exception to this law, that there is some *channel* loyalty, so that duplication is higher between programmes within a channel than between channels. They also report that channel loyalty is rising in line with fragmentation. When faced with a large number of choices, viewers seem to limit themselves habitually to a learned set of familiar alternatives. Lees and Wright (2013) find the same pattern, but less pronounced, in radio listening between music and news channels. It is not known if this law holds for the in-app audience, but if so, it would suggest that for contextual scheduling it would be important to spread the buys over several categories of app (e.g. games, fitness and social media) rather than a single app to accumulate reach over frequency, hence the third question:

RQ3. To establish whether the duplication of viewing law applies to mobile app usage.

Method

Extension and replication of empirical generalisations

To answer the three questions, the approach was to extend empirical generalisations (see Sharp *et al.*, 2017), to establish whether their explanatory theory could be strengthened by extension to mobile app usage and contextual targeting decisions.

Approach and measures

Testing the laws required only reach and session data on the set of apps that compete in a fixed observation period across a potential audience. Such data are recorded for each app on each smartphone in a screen-time analysis easily accessed by users. The method was to create a panel of respondents willing to share that data, such that it could be aggregated to a market level. A quota sample of Generation Z students was therefore recruited, willing to share their data over seven days.

Data collection was managed to minimise panel dropout and 110 usable diaries were collected, recording nearly three thousand hours of on-app screen time. Data were filtered for apps that carry advertising, then aggregated for analysis to summarise:

i. The leading apps across the sample, with the installed penetration of each
ii. Total hours spent on those apps, and their share of viewing.
iii. The proportion of the panel that used each app during the week (Reach).
iv. The average time spent on each app by its users during the week (Engagement)
v. Behavioural segmentation of each app audience by gender.

The analysis was conducted by observation of patterns and relationships in the data and by fitting simple models. We now describe findings in response to each research question, continue to discuss their implications, and conclude with questions for further research.

Findings

Responding to the first research question, we report the behavioural characteristics of Generation Z app users, describing their interactions with categories of app.

App usage varies greatly by share of viewing, but far less in reach and engagement. Our typical panellist spent over four hours a day on a mobile device, in line with recent global industry research (Snapchat, 2019). Due to the size of the panel, and a long tail of small apps, analysis was restricted to 23 leading apps, in six categories, accounting for 2,977 hours of "app-time" with the smallest accounting for less than a 1% share. The average panellist spent over 27 hours on different apps over seven days (Table I) in 3.6 categories.

Table I about here

Table I shows that categories of app vary widely in reach. Social media was accessed by all panellists at least once during the week but dating apps by just 21%. The distribution of audience session time over categories in Table 1 would be a familiar picture for TV schedulers. In television, major stations still gain close to 100% reach each a week, while smaller reach half the population or less, but with share of viewing only in single digits.

In common with television viewing, the audience for apps divides its attention during the week between several categories, just as a TV audience watches sport, current affairs, reality TV and costume drama. We examine *individual* app usage in response to the second and third questions, but here by category we see for example that almost all respondents used music and video apps, but only for some of the time, while only half the panel used games or fitness apps. It is therefore unlikely that a typical "Spotify user" *could* be in a segment, although categories such as gaming or fitness might be segmented by gender, therefore we next examined category audience composition and usage.

Table II about here

Differences in user composition were negligible. Men spent a little longer on apps than women, but viewing time was distributed in much the same proportions. Women spent a little more time on social media and in games apps, and while almost 20% of the sample accessed a dating app, women spent half as much time on them as men, and nobody spent much time on them at all. There is little evidence for category segmentation by gender.

Tables I and II suggest that the share of total use attracted by any app within the category follows the regular pattern seen in TV research – that lower-rated programmes are smaller not because they attract a discrete audience segment who view nothing else, but because they attract *some* viewing time in the wide repertoires of a large proportion of the total audience.

The Law of Double Jeopardy predicts engagement with mobile apps.

In response to the second question, and to examine the contextual targeting proposition, the Double Jeopardy model was fitted across all apps. The main finding is that engagement (viewing time) is predictable.

Weekly reach varied widely across the 23 apps in the data, from just 10% up to 99%. The social media apps, Snapchat, Instagram, Facebook, Twitter, plus TikTok, were each used by over 94% of the panel. YouTube (85%) and Netflix (70%) reached fewer users, followed at some distance by Spotify (57%). The reach of individual apps ranking below this fell rapidly as Figure 1 shows, but not engagement (the curve is almost flat from 10% to 85% reach).

This is a Double Jeopardy relationship (see Barwise and Ehrenberg,1988, Figure 6.1) in which smaller TV channels, radio stations, or programmes vary greatly in the number of people watching them, but very much less in the rates at which they do so. Engagement with any app is, therefore, a function of its reach and not its content.

Figure 1 about here

Model estimation is close to observed outcomes, although the five biggest apps show somewhat *lower* than expected engagement, a systematic limitation at high penetrations (Graham *et al*. 2017). Comparing mean values on these five apps with the total sample, smaller apps have a third of the reach and about a third of the engagement, but with Instagram engagement an exceptional outlier.

Duplication of Viewing predicts audience sharing

The Duplication of Viewing Law states that sharing of users is in line with reach; in response to the third question, it described the data well – an app shares more of its audience with bigger apps, and less with smaller – again, not with particular *characteristics* of rival apps. Appendix 1 shows the full duplication matrix. It records the proportion of the users of any given app (reading down) that also used the apps named, reading across the row. The expectation is that there will be little variation within each column and that the duplication (column) averages decline systematically with reach. Both patterns hold closely. Average audience duplication between any pair of apps in a week is 43%, close to the 37% audience duplication between websites reported in Webster & Lin (2002).

Sharing is summarised in the duplication coefficient, D, the average duplication divided by average reach. The resulting coefficient is managerially useful in calculating unique reach for a given campaign since it predicts the duplication of viewing between any pair of apps. The matrix shows a D value of 1.01 that predicts column averages closely and replicates the original finding for TV viewing in Goodhardt (1966).

What does this ratio mean? It indicates that a user of any app has about the same chance as anyone else in the population of using any *other* app during that week. In other words, a user of the *Bet2Go* sports betting app is no more nor less likely to order a pizza through *Deliveroo* than anybody else, just because they are a user of *Bet2Go*. For advertisers in social media the matrix therefore demonstrates that little additional reach is available on smaller apps, but advertisers on those smaller apps will reach some users of every social media app - not a segmented and "engaged" audience – just a smaller one.

Despite overall consistency, the matrix features deviations for individual apps, indicating a type of format partitioning identified by Lees and Wright (2013) in the radio market, and Sharp, Beal and Collins (2009) in TV. Both report some partitioning between channels such that listeners or viewers were a little more likely than expected to switch within that format.

Table III about here

Adopting their method, we summarise user duplication by category and identify a similar pattern here. Table 3 gives summary statistics within and between each category; the average duplication (AD), the duplication coefficient (D) calculated on those apps, the correlations (r) between observed and predicted duplications and mean absolute deviation (MAE). For interpretation, Lees and Wright (2013) describe AD and r as measures of association and MAE as a measure of variance.

In the top left of the table (Social Media and Entertainment), we see that in all four quadrants average duplications reflect category reach, all correlations are high, and absolute errors are relatively low in comparison to AD. The Law holds at the category as well as the app level; users are shared in line with category reach. But because the correlations are higher and the error lower within than between the categories, switching is a *little* more likely than predicted within the categories, even allowing for their size, although they are competing much as expected. The same pattern is replicated across four categories shown.

For game users there are higher error values in the predictions for individual apps (reflected in summary MAE's). This may be a reflection of a fad, in that games apps are often quickly played out; it might suggest some segmentation by type of game, or it might be sample error since some games had very low install rates. Whatever the source of the bias, although a larger panel size would clarify its underlying cause, for advertisers it is hardly substantive in comparison with the bigger picture this law reveals – size is more important than content.

Discussion and Conclusion

Fundamental change in the online environment means that the audience for advertising is moving into mobile apps, which do not support third party cookie tracking. Instead, mobile apps use device ID which relieves privacy concerns and delivers better-quality advertiser data (Neumann *et al,* 2019; Rafieian and Yoganarasimhan, 2020; Ryan, 2020). Walled garden platforms will continue to offer behavioural targeting to their advertisers large and small, while finding new solutions to the problem of user privacy, but much of the ad-tech industry is now proposing contextual targeting. Their sales pitch is that segmented users can be found and targeted on relevant apps, and therefore contextual targeting is a substitute for the behavioural alternative. In this study we have questioned that assumption.

We examined app usage over seven days for a Generation Z segment, using aggregated screen time data. The main finding is that Generation Z uses apps in much the same way as any population uses mass media such as radio or TV, and so despite publisher claims, individual mobile apps are quite unlikely to deliver a segmented audience to advertisers. The

Law of Double Jeopardy applied closely, therefore reach predicts screen time, with the exception that screen times on the very largest apps are significantly *over*-predicted. There is therefore little evidence for unusual engagement on any app, while the Duplication of Viewing law described audience sharing quite well, including between formats. In sum, individual users have different preferences for the apps they access, and those apps compete with each other for the time the audience devote to them; but while use is highly fragmented, only apps with higher reach are systematically used for longer.

This does not mean that contextual targeting is inefficient – far from it – rather, it raises the issue of appropriate and consistent metrics across advertising formats. Behavioural targeting delivers immediate and measurable behavioural response, but this is hardly surprising because it simply identifies the highest propensity buyers, those closest to a purchase or other action and nudges them to take that action. Fulgoni (2018) classes this as "sales lift" advertising but makes the point that brands *also* need "brand lift" – investment in the future purchasing of the far greater number of brand users with low or very low propensities.

Offline this type of outcome is long term and delivered through accumulated campaign reach (e.g., Ehrenberg, 2000; Sharp, 2010). Contextually targeting brand consumers in mobile apps can build this reach in much the same way as a TV audience does, because total audience for in-app advertising is comparable in size and engagement to that for TV (MacKay, 2019; O'Dea, 2020). Indeed, Facebook already offer reach campaigns of this sort to the biggest CPG brands, yet in practice, over half of US media directors use only behavioural ROI metrics to evaluate digital scheduling (Cheong *et al,* 2010), and this makes relative efficiency between media impossible to measure (Binet & Carter, 2018), creates a bias towards short term objectives rather than longer term outcomes, and encourages a habit that marketing practitioners may find hard to break.

Our findings help resolve these issues for those pioneers looking for reach in apps rather than "intent", because robust knowledge exists that can be applied to the interpretation of audience behaviour. For example, our findings about the distribution of audience over competing apps resemble the fragmentation of the TV audience. On TV the highest rating shows are becoming expensive for advertisers, and online impressions in high reach apps are desirable for the same reason (they attract the lightest app "viewers"); but impressions in these apps may now be priced cheaper than the "specialist context" offered on less popular vehicles. Again, if apps are offered to market on the basis of user engagement, then it is a simple matter to test this using the Double Jeopardy law – apps with lower reach will simply engage audiences less and not more. The law can then be used to establish realistic relative bid levels. Finally, the main finding in the duplication analysis was that audience duplication appears higher within than between app categories. That means that a media schedule can gain some advantage if it buys impressions across categories. This makes it easier to build reach over duplication, rather than focussing on a single app or category which has a bias towards duplication.

Theoretical Contribution

The study advances explanatory theory of audience behaviour, extending it to a novel media context. Extending existing theory is preferable to creating new theory because the laws presented here are known to be robust and in widespread commercial use. They also support a range of *other* models in consumer behaviour (e.g. Ehrenberg *et al,* 2004; Sharp, 2010) which together form a coherent explanation of how advertising works (Ehrenberg, 2000). These linkages bridge the divide between old and new media providing a common conceptualisation and metrics for academic modellers to evaluate omnichannel communication theory.

Practical implications

For managers, the findings might be surprising because so much digital marketing rhetoric revolves around audience engagement and micro-targeting. Nevertheless, the fact that the marketing laws describe behaviour so closely indicates the likely existence of a fallacy in that logic. Except for the global giants, most apps have very low reach even after a week. After seven days, the biggest gaming app in our data had been opened at least once by just 15% of the panel; many apps were even smaller. The same was true for most fashion, fitness, and food delivery apps. However, this does not imply a specialist audience on that app; the fit of the models predicts the engagement with any app on the basis that its users are unsegmented, and so attention is built widely in the way it is for a TV audience.

This is important to realise because in-app advertising is no longer only used to promote other apps or games – global brands in FMCG, retail fashion, travel, cosmetics, and cars use the medium. Findings show that campaigns in these fields need not be restricted to sales lift objectives from tightly targeted segments; effective reach can equally be scheduled from smaller apps to obtain brand lift objectives.

Limitations and future research directions

We have been able to demonstrate important regularities in online audience behaviour that can be easily accessed by advertisers. Analysis of more granular datasets and in other regions is now desirable to extend the findings. However, the main story is probably already contained here: that the audience for in-app advertising is no different from that delivered by any other mass media, even though it is highly fragmented.

Our method was limited in scale and conducted with a broad brush, limitations that now serve to define further studies. First, we call for further tests in commercial datasets and with a focus on a broader range of audience characteristics to evaluate the partitioning of apps, or categories of apps, in more detail. Second, those studies should extend to other territories, to enable comparisons between countries or regions where contextual factors may affect the stochastic assumptions of the models and signify boundary conditions to the theory. Further, and more detailed questions would then follow.

For example, timing effects are a fruitful area of research. Access to an "always on" in-app audience through analysis of day-parts may be interesting, not based on its higher or lower buying readiness, but based on an additional frequency that might be obtained with no loss of reach. McDowell & Dick, (2005) identified a daypart Double Jeopardy effect whereby a TV audience is retained on a channel beyond the duration of a single programme, which can therefore be reached at a higher frequency. This so-called lead-in audience retention was later modelled for prime-time TV by Jardine *et al*. (2013) and found to depend on the higher or lower rating of the earlier or later programme. Certain apps, or categories of app, may also retain or lose audience systematically at different times of day. Knowledge of this would help tailor a media buy, either for increased frequency or additional cumulative reach.

Multi-channel effects have been evaluated successfully with the models used here, and their use should be extended to include in-app audiences. Taylor *et al*. (2013) examined cross-media sales effects between TV and website advertising in single-source data and found (1) that the extra reach was mainly duplicated, but (2) that sales effects from a single online exposure were less consistent than those from TV. Further research might now confirm these effects for in-app advertising.

Finally, and crucially for researchers and practitioners, consistently measuring unique reach across digital media has become almost impossible. This is partly due to the walled gardens maintained by major platforms. For example, at the time of writing TikTok does not give advertisers third party verification of monthly active users and Instagram does not report comparative platform data. The extent to which online counts may no longer represent human activity is also unknown (Nelson-Field, 2020). New methods are needed to validate unique reach across media, and perhaps as with this panel, those methods need not be entirely new.

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APPENDIX 1: Duplication of viewing for 23 apps over one week

% of users of X	Reach	% who also use Y Snp	Inst	FB	TT	Tw	YT	NF	Sp	Fit	LK	Kl	Ti	UD	Cl	8b	Sc	EB	Be	BF	JE	RR	CM	UN	Avg
Snapchat	99		97	96	94	94	85	70	57	54	43	27	23	18	17	14	12	12	12	11	11	11	10	6	40
Instagram	98	99		97	94	93	85	69	58	54	43	26	21	20	18	14	12	12	12	11	11	10	10	7	40
Facebook	97	99	98		93	93	86	71	58	54	44	27	24	20	18	14	12	12	12	11	10	11	10	7	40
Tik Tok	94	99	98	96		93	85	71	59	55	43	27	23	20	18	16	10	13	13	11	12	11	10	6	40
Twitter	93	100	97	96	93		84	70	55	54	44	26	21	19	18	13	12	12	13	12	11	12	9	6	40
Youtube	85	99	97	97	94	93		69	60	55	41	24	26	19	18	15	11	14	13	12	11	9	10	6	40
Netflix	69	99	96	97	95	94	84		60	56	39	29	27	16	18	13	13	14	13	6	13	9	9	5	41
Spotify	58	98	98	97	97	90	89	73		60	41	24	29	13	17	10	14	11	13	6	11	10	13	11	42
Fitness App	54	98	97	95	95	93	87	72	63		37	22	22	22	18	12	8	8	17	10	13	7	8	8	41
Linkedin	43	98	96	98	92	94	81	63	54	46		33	23	19	27	19	15	13	8	15	13	8	8	6	42
Klarna	26	100	97	100	97	93	79	76	52	45	55		24	28	31	14	7	17	14	21	0	17	14	7	45
Tinder (or any dating app),	21	100	92	100	96	88	96	84	72	52	44	28		12	12	20	12	20	16	12	8	8	12	4	45
Unidays/ Student Beans	20	95	100	100	100	95	86	57	38	62	43	38	14		24	19	10	14	10	14	10	19	14	0	44
Clothing App	18	100	100	100	100	100	89	74	58	58	68	47	16	26		16	0	16	21	21	16	16	0	5	48
8 Ball Pool	14	94	94	94	100	81	88	63	38	44	56	25	31	25	19		19	13	6	13	0	19	13	6	43
Scrabble	12	100	100	100	77	92	77	77	69	38	54	15	23	15	0	23		0	0	0	15	8	8	0	41
Endless Balls	12	100	100	100	100	92	100	85	54	38	46	38	38	23	23	15	0		8	8	23	15	23	8	47
Sky Bet/Bet 2/ Betting App	12	100	100	100	100	100	92	77	62	77	31	31	31	15	31	8	0	8		8	15	8	0	0	45
Bottle Flip	11	100	100	100	92	100	92	42	33	50	58	50	25	25	33	17	0	8	8		0	0	25	0	44
Just Eat/ Deliveroo	11	100	100	92	100	92	83	83	58	67	50	0	17	17	25	0	17	25	17	0		8	0	0	43
Run Race	10	100	92	100	92	100	67	58	50	33	33	42	17	33	25	25	8	17	8	0	8		8	8	42
Coin Master	10	100	100	100	91	82	82	64	73	45	36	36	27	27	0	18	9	27	0	27	0	9		9	44
UNO	7	100	100	100	86	86	86	57	100	71	43	29	14	0	14	14	0	14	0	0	0	14	14		43
Average	**42**	**99**	**98**	**98**	**94**	**93**	**86**	**69**	**58**	**53**	**45**	**29**	**23**	**20**	**19**	**15**	**9**	**14**	**11**	**10**	**10**	**11**	**10**	**5**	**43**
Predicted Duplication:		**100**	**100**	**99**	**96**	**95**	**87**	**71**	**59**	**55**	**44**	**27**	**22**	**20**	**18**	**14**	**12**	**12**	**12**	**11**	**11**	**10**	**10**	**7**	

Table I. Mobile app category reach and hours used per week

Category	% share of total hours	Weekly reach (%)	Average hours per user/week
Total	**100**	**100**	**27.1**
Social Media	78	100	21.1
Music & Video	11	98	3.1
Games	3	54	1.8
Shopping etc	3	55	1.6
Fitness	3	55	1.4
Dating	1	21	1.6

Panel size: n = 110

Table II. Usage of the main types of app by gender

Gen Z Panel (n = 110)	Average time on apps per week (hours)	Percentage of time spent on…					
		Social Media	Entertainment: Music & Video	Entertainment: Games	Shopping Take-away & Betting	Fitness	Dating
Men	29	77	12	2	3	3	2
Women	25	79	11	4	3	3	1

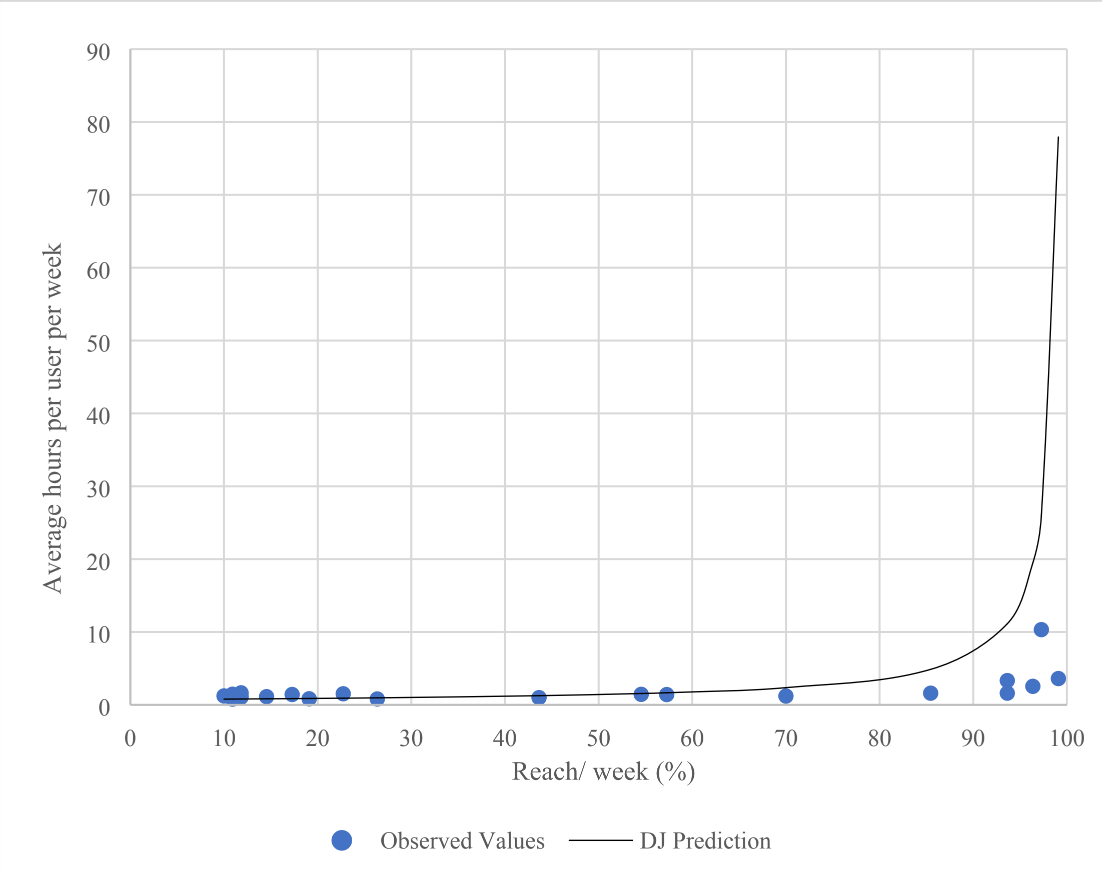
Panel size: n = 110

Table III: Mobile app audience duplication of viewing and deviations by category

	Social Media		Entertainment		Shopping		Gaming	
Social Media	AD=87%	r = 1.0	AD = 70%	r = 0.96	AD = 18%	r = 0.99	AD = 11%	r = 0.99
	D=0.99	MAE=0.8	D = 0.80	MAE=14	D = 0.2	MAE=14	D = 0.13	MAE=10
Entertainment	AD = 87%	r - 0.98	AD = 72%	r = 1.0	AD = 17%	r = 0.99	AD = 10%	r = 0.97
	D = 1.23	MAE=4.8	D = 1.01	MAE=0.66	D = 0.24	MAE=13	D = 0.14	MAE=9.0
Shopping	AD = 90%	r = 0.93	AD = 71%	r = 0.95	AD = 21%	r = 1.0	AD = 10%	r = 0.97
	D = 5.3	MAE=9.0	D = 4.2	MAE=29	D = 1.2	MAE=4.2	D = 0.6	MAE=4.0
Gaming	AD = 87%	r = 0.95	AD = 69%	r = 0.98	AD = 16%	r = 0.95	AD = 11%	r = 1.0
	D = 7.9	MAE=13	D = 6.3	MAE=31	D=1.45	MAE=7.6	D = 1.0	MAE=6.8

All apps: AD = 43% r = 1.0 D = 1.02 MAE = 1.4

Figure 1: Double Jeopardy in mobile app engagement



Engagement is a function of reach, not context.

The Generation Z audience for in-app advertising

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