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THE INFLUENCE OF MOBILE ADVERTISING ON PURCHASE INTENTION

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Dissertation presented as the partial requirement for obtaining a Master's degree in Information Management

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Abstract

Mobile advertising has seen explosive growth in the last decade. Advertising delivered on a mobile devices account for the majority of total internet advertising revenues. There is a pressing need for researchers to better understand what makes mobile advertisements successful. For this purpose, I propose a conceptual model that encompasses Ducoffe's web advertising model, interactivity and flow experience theory. Based on the data collected of 208 respondents through an online survey, I empirically tested the conceptual model using partial least squares method (PLS-SEM). The results suggest that perceived advertising value and flow experience are positively associated with consumers' purchase intention, which is consistent with previous studies. The findings also contribute to the existing mobile advertising literature by exploring perceived interactivity as an antecedent to flow experience. When exposed to mobile advertisements, consumers' state of feeling in control coupled with the ability to instantly receive feedback from the advertiser seems to facilitate a flow state, which in turn increases the purchase intention.

Keywords

Ducoffe Web Advertising Model

Advertising Value

Flow Experience

Perceived Interactivity

Mobile Advertising

Purchase Intention

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1. Introduction

In 2018, according to IAB Internet Advertising Revenue Report, mobile advertising revenues amounted to $69,9 billion which represents 65,1% of total digital advertising revenue in the United States. Moreover, whereas the industry's total growth boasts a compounded annual growth rate (CAGR) over the past ten years of 16,8% and is expected to surpass traditional advertising in the US for the first time in 2019, the key driver has been mobile advertising, growing with a CAGR of 53,8% over the past five years. As mobile advertising is on the rise to become the most important advertising category, so grows the need to further research the factors that have the strongest impact on its success. According to the first-quarter 2018 Nielsen Total Audience Report, US adults spends on average just over 11 hours a day consuming and interacting with media via devices. Time spent on mobile devices (app/web on a Smartphone/Tablet) accounts for more than a quarter of the total time spent (28%), whereas for the age group 18-34 that percentage increases up to 36% - highlighting the shift of usage in demographics to mobile compared to immobile devices.

Mobile advertising, as defined by the Mobile Marketing Association, is "a form of advertising that transmits advertisement messages to users via mobile phones or other wireless communication devices" (Chen & Hsieh, 2012). Researchers have formerly differentiated between push and pull types of mobile advertising. Push advertising messages require no prior consent from the user and are usually in the form of SMS or MMS. Pull advertising messages allow users to browse content on their own and are presented with mobile advertisements (keyword search, display, mobile game, and rich media advertising) (Chia-Ling et al., 2012; Xu et al., 2008). In the more distant past, research in consumer attitudes and preferences towards mobile advertising has been focused heavily on push-based advertising and dominantly in the form of SMS messages (Leppäniemi & Karjaluoto, 2005; Chia-Ling et al., 2012; Bacile et al., 2014). However, the rise of apps and social networks such as Facebook, Twitter or Youtube has directed mobile advertising budgets towards more rich media advertising. These platforms attract hundreds of millions of consumers on a regular basis and employ business models that are overwhelmingly centered around advertising. Furthermore,

they also provide advertisers with incredible audience targeting opportunities and tremendous insights through their analytic capabilities (Dhruv et al., 2016).

Considering the ultimate goal of advertising is to entice consumers to purchase products or services offered by brands, it is important to identify the factors that influence the buying process. More recently, most of the prior research has focused on the following end goal concepts: purchase intention, attitude towards advertisement or behavior-based metrics (such as click-through or conversion rates) (Bart et al., 2014; Lee at al., 2018; Martins et al., 2019;). Ghose et al., (2013) deal with both click-through and conversion rates for consumers shown mobile display advertisements. Bart et al., (2014) investigate the effectiveness of 54 brand campaign offerings and measure differences in brand attitudes and purchase intentions in a post-hoc survey. Others have conducted surveys or experiments to examine the factors affecting attitudes towards advertisements (Kim et al. 2019; Shareef et al., 2017). There has also been substantial research in online advertising focusing on advertising value, a construct derived from Ducoffe's web advertising model. This has provided insight on the importance of several elements that contribute to advertising value such as entertainment, informativeness, credibility and irritation (Ducoffe, 1995; Kim 2019, Liu et al., 2012; Kim & Han, 2014). Another concept that has been explored as a predictor to purchase intention is perceived interactivity, which positively affects tablet users when investigating what makes them more likely to purchase mobile apps (Lee at al., 2018). Moreover, another factor considered was flow experience, Martins et al., (2019) presented findings that suggest flow positively influences consumers' purchase intention. Lastly, Rodríguez-Ardura et al., (2016) conclude that perceived interactivity in e-learning context is positively associated with, and could be a potential antecedent that facilitates consumers' flow experience.

However, despite a growing body of literature, most of the research conducted on the online advertising field is not based explicitly on a particular theory or refers to a specific model in order to generate testable hypotheses (Knoll, 2015). Although it is beyond the scope of this study to consider all the above-mentioned variables in play, this thesis aims to unite the concepts deriving from online flow theory & Ducoffe's web advertising model in order to improve the current understanding of the drivers of purchasing decisions in the mobile context. Additionally, it explores interactivity

theory and assess perceived interactivity as a potential catalyst to flow experience according to findings and suggestions by previous researchers (Wu et al., 2005; Novak et al. 2003). In summary, it delves into the general perception of online advertising fixating on advertising experienced on mobile devices.

The master's thesis as structured as follows: Section 2 explains the purpose of the study. Section 3 reviews the existing literature detailing the evolvement of interactivity, flow experience and advertising value throughout the years in the research world. Then, section 4 includes the research questions and the proposed conceptual model. Sections 5,6 & 7 cover the data collection process, methodology and descriptive statistics of the dataset obtained. Sections 8, 9 and 10 contain the data analysis and structural model results. Finally, section 11 contains the conclusions along with theoretical and practical implications.

2. Purpose

This study focuses on four key issues. First, it dives into exploring perceived interactivity as an antecedent to consumers' online flow experience. Second, following Ducoffe's web advertising model, it considers informativeness, entertainment and credibility as predictors of advertising value in the mobile advertising space. Third, it explores the impact experiencing online flow has on their purchase intention. Fourth, it looks into the effect of advertising value on flow experience and purchase intention.

The purpose of this research is three-fold. First, this research aims to fit a theoretical gap in mobile advertising research by providing a model that unites several concepts that have been previously explored separately. Second, it strives to examine interactivity as a possible factor to induce flow experience in consumers at the time of advertisement consumption. Third, it hopes to provide a guideline for marketers and professionals to understand the importance of consumers' perceived interactivity, perceived advertising value, flow experience when exposed to mobile advertisements as drivers of their intention to purchase.

3. Literature Review & Hypotheses Development

a) Purchase Intention

Purchase intention represents the possibility that consumers will plan or be willing to purchase a certain product or service in the future (Wu et al., 2011). Higher positive levels of purchase intention indicate an increase in the possibility of purchasing. Additionally, when consumers have positive purchase intention, this creates a positive brand commitment ensuing consumers to make a purchase (Schiffman and Kanuk, 2007). Regarding the context of smartphones, one needs to consider purchase intention as the desire of consumers to make a purchase through the mobile application (Martins et al., 2019).

b) Perceived Interactivity

Interactivity as a concept appears in multiple fields of research such as information science, human-computer interaction, interactive marketing, industrial design etc. (McMillan, 2002). Furthermore, even within the context of consumer behavior in a digital environment, interactivity has been variously defined depending on the context and goal of the research. One commonality across different definitions is that it encompasses communication between the user and another party. Unlike traditional media that have a one-way information flow, the internet allows users to experience interactive, bidirectional and many-to-many communications (Hoffman, Novak & Chaterjee, 1995).

McMillan, (2002) identifies three traditions of research on interactivity: user-to-user, user-to-content & user-to-system. The first type (user-to-user) refers to users engaging in communication between themselves and can exist both in offline and online circumstances. In an offline context, Yoo et al. (2010) refers to user-to-user communication as being mainly direct face-to-face conversation. As an example, consumers may form groups where they can interact with one another based on similar interests for a certain product or service. With regards to online context, user-to-user interaction occurs through technological platforms such as email and chat rooms and represents computer-mediated communication (Park et al., 2020). In the context of mobile advertising, online advertising on Amazon's network (twitch.com) allows for

users to interact with one another through a chat room while consuming an advertisement.

The second type (user-to-content) refers to the user interacting with the content and the content creator. Chen et al. (2005) explored user-to-content interactivity through testing various levels of customization at an online apparel shop where research participants could create models that match their physical characteristics. The third type (user-to-system) tend to dive into issues such as interfaces, input devices, navigation tools etc. The table below presents an overview of the three different categories including the interactive features and user actions together with their perception towards them.

	Interactive Features	**Perceived Interactivity**	**Interactive Exchange**
User-to-User	Chat room	Perception that presence of chat space makes a site interactive	Participating in an online chat
User-to-Content	Customer reviews	Perception that customer reviews enhance interactivity of site	Posting a product / service review
User-to-System	Web-based forms	Belief that Web-based form will elicit a response	Filling in a web-based form

Table 1: Three Traditions of Interactivity. *Adapted from (McMillan, 2006)*

However, these three categories can sometimes overlap and as such serve more as a basic framework to distinguish between the different areas of focus in terms of interactivity. For example, while sponsored content on Google's network (including google.com, youtube.com etc.) can represent user-to-content interactivity, advertisements on Facebook's network (facebook.com, Instagram.com etc.) allow for interaction both between users (e.g. via comment section) & with the content creator/advertiser (user-to-content) simultaneously. Park et al. (2020) explored user-to-system interactivity in the AR space and excluded the communication element from

their research model due to the nature of interactivity. In this study, the focus is a mixture of user-to-user and user-to-content creativity as both are present within mobile advertising.

In differentiating between how interactivity would be considered in old media versus new media, some researchers have considered interactivity as a feature or characteristic of a medium: "Interactivity is a function of three things: (1) the speed with which content can be manipulated; (2) the range of ways in which content can be manipulated; and (3) mapping, or how similar the controls and manipulation in the mediated environment are to controls and manipulation in a real environment (Steuer 1992, Coyle and Thorson 2001). Other researches have opted for a broader definition: "Interactivity is an expression of the extent that in a given series of communication exchanges, any third (or later) transmission (or message) is related to the degree to which previous exchanges referred to even earlier transmissions (Rafaeli, 1988).

Another stance on interactivity, which is examined in this master's thesis, is focusing on how users perceive and/or experience interactivity. The focus on perception is consistent with marketing, advertising, and communication traditions (Gao et al., 2010). Furthermore, the extent to which consumers perceive interactivity is subjective and thus not necessarily the same as the actual level of interactivity available on digital channels (Song and Zinkhan, 2008; Park et al., 2020). Kim et al. (2015) argued that interactivity cannot be defined as a single dimension, but rather through multiple dimensions in view of the evolvement of communication technologies over the last decade (Bao et al., 2016; Tan et al., 2018).

However, there exist differences even within the approach to researching perceived interactivity. Although most researchers consider it a second order construct, there have been various efforts in identifying the most appropriate sub-constructs. The most common concepts found in the literature are the following three: user control, two-way communication & synchronicity (McMillan, 2002; Gao, Rau, & Salvendy, 2010, Lu et al, 2019; Wu 2017; Yoo et al., 2010; Lowrly et al., 2009; Park et al., 2020; Tan et al., 2018; Bao et al., 2016).

- **User Control**

This sub-construct refers to the degree to which a consumer can select the content, timing and sequence of an advertisement to control their viewing experience. In an interactive setting, users should be able to feel in control over the information exchange. For mobile communication, perception of full control over the content and the conversation on handheld devices is even critical, because handheld devices are often very personal gadgets. Users will feel quite annoyed or even furious when they find that they can do nothing with the messages pushed into their cell phones (Gao et al., 2010).

- **Two-way communication**

Communication is considered interactive when it allows for reciprocity between the parties and the messages should be in sequence such that they are related. In other words, the setting should allow users to communicate with the advertiser back and forth. Both sides should be active senders and receivers (Gao et al., 2010; Bao et al., 2016). Mobile products, especially smartphones, should fit this criterion well since they were originally designed for a two-way conversation via voice and people are much more used to giving feedback with their phones than their PCs (Gao et al., 2010).

- **Synchronicity**

Synchronicity refers to the extent to which the communication occurs without any delay (Wu et al., 2017). It refers to the speed at which the messages can be delivered and at which persons can process messages. The faster the response, the greater the perception of interactivity (Gao et al., 2010).

As these three concepts appear most frequently in the existing literature, they are considered as the three sub-constructs for perceived interactivity in this master thesis.

c) Flow Experience

The flow construct, also referred to as “optimal experience”, was first introduced by Csikszentmihalyi (1975) and refers to “the holistic experience that people feel when they act with total involvement”. In other words, experiencing flow means getting completely immersed in a certain activity – “being in the zone”. According to Csikszentmihalyi (1997) in moments such as these what we feel, what we wish and

what we think are in harmony. A person in flow is fully focused, has no room for distracting thoughts or irrelevant feelings and the sense of time is distorted. The state of flow can be experienced in various types of activities from playing a chess game to engaging in a social interaction. Characteristics of a flow-inducing state include:

i) Clear set of goals that require appropriate responses: regardless of whether it's playing tennis or writing computer code, such activities provide players with clarity on what should be done and how.

ii) Immediate feedback: after each move of a chess game, players can tell whether they have improved their position or not.

iii) Quality of experience: a person's skills need to be fully involved in overcoming challenges that are just about manageable. Optimal experiences occur when both variables, skills & challenges, are high.

The figure below presents a 9-Channel Model where flow is described through perceived challenges and perceived skills. Additionally, achieving optimal experience does not depend on how skilled or how challenging the opportunity is objectively, but rather how the person perceives both.

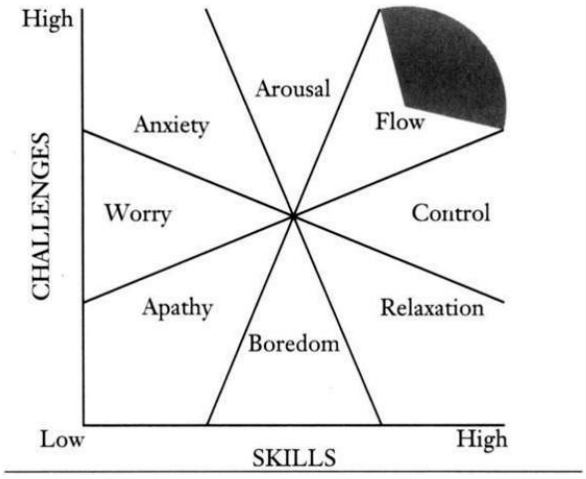

Figure 1: 9-Channel Model. Adapted from (VIassimini & Carli, 1988)

When individuals face certain opportunities – they assess whether they have the appropriate amount of skill to deal with those challenges. When a person deems their skills low and the challenge moderate to high, they would likely find themselves in a state of worry or anxiety. On the opposite side, if a person thinks their skills are more than adequate for the challenge, they could feel relaxation or boredom. When both

perceived skill and challenge are low, one finds themselves in a state of apathy. Flow is achieved through the balance of high challenge with high skill. In order to achieve flow, individuals need to either increase their challenge or learn new skills.

In the decades to follow, flow has been researched in the context of marketing, advertising and consumer behavior in a computer-mediated environment. Hoffman & Novak (1996) extended flow theory to a digital environment (World Wide Web) and suggested that digital marketers' success depends on how well they can create opportunities for consumers to experience flow. They defined the flow construct in a computer mediated environment as the state occurring during network navigation, which is (1) characterized by seamless sequence of responses facilitated by machine interactivity, (2) intrinsically enjoyable, (3) accompanied by a loss of self-consciousness, and (4) self-reinforcing. In order for users to achieve this state, two primary criteria need to be satisfied: (1) consumers have to concentrate on the interaction to the extent where they only experience relevant thoughts to the activity being performed, and (2) consumers must perceive a parity between their skills and challenges of the activity. Additionally, they suggest interactivity and telepresence as secondary antecedents of flow i.e. catalysts that increase the subjective experience of the user's flow. Although they are not sufficient on their own to induce a state of flow, these constructs aid in allowing users to focus their attention and perceive coherence between their skills and challenges.

In terms of how consumers make use of their time in a computer mediated environment, Hoffman & Novak (1996) suggest two types of behaviors: goal-directed & experiential-directed. Goal-directed and experiential behavior are characterized respectively by (1) extrinsic versus intrinsic motivation, (2) instrumental versus ritualized orientation, (3) situational versus enduring involvement, (4) utilitarian versus hedonic benefits, (5) directed versus nondirected search, and (6) goal-directed versus navigational choice.

Goal-directed behaviors include users attempting to complete a certain task such as buying a product online, whereas experiential-directed behaviors refer to activities that are not guided by goals or outcomes, but by the process itself (Bloch, Sherrell, and Ridgway 1986, p. 121). Example of an experiential behavior includes users engaging

in an online activity such as consuming content on a website with no specific goals in mind. Hoffman & Novak (1996) initial's hypothesis that flow may occur in both goal-directed and experiential-directed behaviors was shown to be correct (Novak et al., 2003), however the results suggested that goal-directed activities have a stronger effect in producing flow than activities done just for fun.

Taking a look at other studies, flow has been measured directly with enjoyment and time distortion in the context of transaction intentions of online travel community members (Wu et al., 2005). The findings of this study also suggest that interactivity is a critical factor to inducing flow, which in turn increases transaction intentions. Ho et al., (2010) measure flow directly with control, concentration, curiosity and intrinsic interest present results that point to the positive relationship between flow and e-learning outcome. Additionally, a positive relationship between interactivity and flow is also suggested by the results. Similarly, most recently, Martins et al., (2019) found flow experience to be positively associated with both advertising value & purchase intention. Consistent with the previous studies, in this master thesis flow is directly measured with time distortion, concentration & enjoyment. Thus, the following three hypotheses are proposed:

- **H1.** *Perceived Interactivity is positively associated with Flow Experience*
- **H2.** *Flow Experience is positively associated with Purchase Intention*

d) Perceived Advertising Value

Advertising Value as a construct was first introduced in 1995 by RH Ducoffe in order to represent the perceived value of advertising to consumers. Advertising value is defined as a subjective evaluation of the relative worth or utility of advertising to consumers (Ducoffe, 1995). The original model of advertising value includes the following antecedents: informativeness, entertainment & irritation. Informativeness refers to the ability of advertising to inform consumers of product alternatives so that consumers can make purchases that yield highest possible satisfaction. Irritation arises when consumers are annoyed, insulted, offended or feel manipulated by certain advertising techniques. Irritation has been empirically found to have a negative impact on advertising value (Ducoffe, 1996). Entertainment refers to the extent to which an advertisement is deemed pleasant or likable.

The first study done on advertising value by Ducoffe was conducted by administering a mall-intercept survey in two shopping malls. The subjects were asked to communicate their reactions to scale statements by considering their thoughts towards advertising in general and not a specific advertisement for a product or service. The objective was to figure out if there were grounds for a general criterion that could explain the value of advertising across different product divisions. As previously hypothesized, the results showed significant relationships between informativeness, entertainment and irritation and advertising value. Additionally, in order to take into account the influences of the variables informativeness and entertainment towards a particular advertisement of a product or service, a follow up study was done to assess consumers' reaction towards preselected advertisements that fit into 4 categories: high-high informativeness; high informativeness – low entertainment; low informativeness – high entertainment; high-high entertainment. The results were consistent with the previous study and indicated that both variables have a significant positive influence on the value of the advertisement. This provides some evidence that regardless of whether advertising perceptions are investigated in a general fashion or towards a particular advertisement – the results are in the same direction. As such, in this master's thesis, the approach taken is asking respondents to report their reactions towards mobile advertising in general as it offers more flexibility in the data collection process.

However, there are other factors that could potentially play a role in influencing advertising value. Some examples include the context of the medium in which the advertisement is displayed, the attitude towards the advertiser or how frequently consumers are exposed to the message. With regards to the media context, in the following year, Ducoffe (1996) applied his model to the web to assess whether advertising on the internet could play a role in obtaining different results. Previous research had indicated that consumers' opinions towards advertisements can differ depending on the type of medium used to convey the message. For instance, in the past consumers had reported they find advertising in newspapers as most informative and reliable while TV and radio scored lower on these aspects. (Becker, Martino, and Towners, 1976; Grotta et al., 1976). Nevertheless, the results of the follow up study once more confirmed the initial hypotheses of the advertising model.

In 2001, Brackett and Carr further validate the previous web advertising model in a study on college student attitudes towards web advertising. Apart from confirming the previous three variables, several other variables are tested to expand the model: credibility and demographic variables (gender, major, class & age). Credibility refers to the extent the ad is believable, credible or trustworthy. As for the demographic variables, the authors hypothesized that gender and major would be relevant and have a significant impact on advertising value whereas class and age would not. The results indicated credibility to be a fourth antecedent to value whereas none of the demographic variables were found to have a significant effect. This evidence is aligned with the purpose of this study, which does not take into consideration participants' demographics as relevant to the matter.

Zhang and Whang (2005) once more confirm the validity of the model by producing consistent results across surveys for both traditional media and internet-based media. Furthermore, they add interactivity as a fifth antecedent and is found to be statistically significant across both groups. Interactivity in this study is considered as content interactivity: measured by two-way communication, control, frequency of exchange & customization. However, even though there are no significant differences between the independent variables for both cases, there are differences in the correlations between them. In particular, entertainment and irritation are not significantly correlated for traditional media, whereas there exists a negative correlation for internet media. The case is the same when irritation and interactivity are considered with only a significant negative correlation arising in the internet media group. More recently, Bevan-Dye (2013) produced mostly consistent results on the same topic by researching Generation Y students in South Africa. In contrast to Zhang and Whang's results, they found the relationships between irritation and entertainment & irritation and credibility as non-significant.

In the context of social media advertising, Dao et al., (2014) exclude irritation and use informativeness, entertainment and credibility to assess advertising value and subsequently purchase intention in Southeast Asian transitional economies. The findings are similar and consistent with previous research suggesting informativeness, entertainment and credibility to be positively associated with advertising value, followed by ad value with purchase intention. Additionally, a more recent study on

social media advertising showed the effect of the same variables when a Facebook user would informally disseminate an influential statement about a product (Shareef et al., 2017). The results indicated that while entertainment and informativeness were significant in their positive impact on value, irritation was not.

Wu et al., (2017) expanded the advertising model to include involvement, personalization and interactivity and point to the complexity of the nature of mobile advertising as they found all of the above to contribute as predictors. Involvement refers to the extent to which the user had previously been involved with the brand. Personalization refers to how well the advertisements fit the recipients' wants and needs. Interactivity follows the same three concepts as considered in this master's thesis. However, on the other hand, they found entertainment and irritation to show a non-significant impact on value. Finally, Martins et al., (2019) found informativeness, credibility, entertainment, irritation and incentives to have a positive impact on ad value, which in turn positively impacts purchase intention.

As shown in the literature review above, there is no exact consensus on the concepts that have originated from Ducoffe's web advertising model. According to the findings of most studies, this research takes informativeness, entertainment and credibility as the three concepts to predict perceived advertising value. Thus, I propose the following three hypotheses:

- **H3a.** *Informativeness is positively associated with Perceived Advertising Value*
- **H3b.** *Entertainment is positively associated with Perceived Advertising Value*
- **H3c.** *Credibility is positively associated with Perceived Advertising Value*

Furthermore, as previously discussed, significant amount of past research has shown the link between advertising value and purchase intention & flow experience with advertising value. Therefore:

- **H4.** *Flow Experience is positively associated with Perceived Advertising Value*
- **H5.** *Perceived Advertising Value is positively associated with Purchase Intention*

4. Conceptual Model & Research Questions

The thesis will consider 10 different constructs: Informativeness, Entertainment, Credibility, Flow Experience, Perceived Advertising Value, Purchase Intention as well as Perceived Interactivity as a second order construct composed of the following 3 subconstructs: User Control, Two-way Communication, Synchronicity. The two research questions can be summarized as follows: "with regards to mobile advertising, (1) how does perceived interactivity impact flow experience; (2) what is the effect of perceived advertising and flow experience on purchase intention of consumers." Figure 1 below presents the conceptual model behind the research. The statistical method used to conduct the analysis is PLS-SEM. All of the constructs are considered reflective factors and as such all the measurement items are expected to have high inner-correlation. Each construct and subconstruct is measured by three measurement items (as shown in the questionnaire – table 2) with the exception of Flow Experience, which is measured by 5 items. The conceptual model is visualized in the figure below.

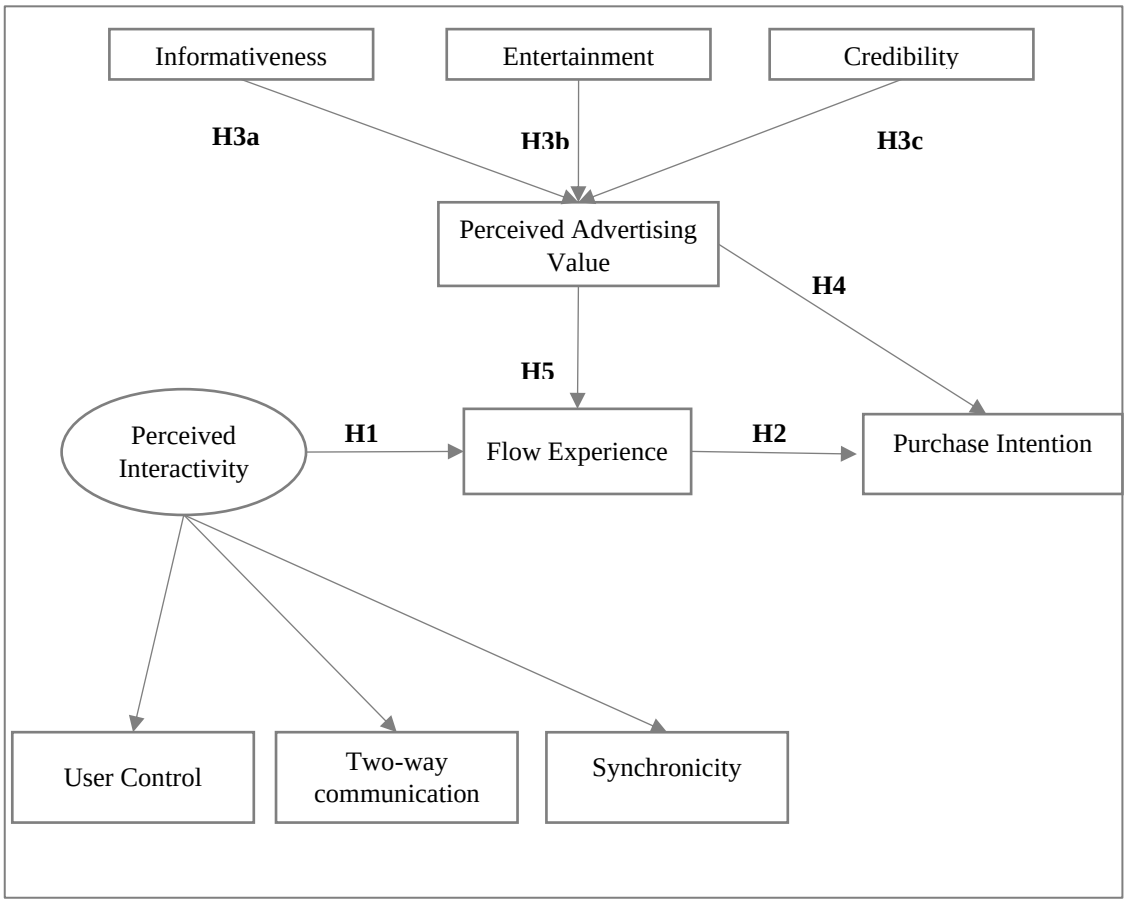

Figure 2: Conceptual Model

5. Data Collection

In order to test the previously suggested model, structural equation modeling (PLS) was used in order to explore the existence of the proposed relationships between the four concepts. An online survey (table 2 below) was created composed of 29 queries on a 7-point likert scale (1 – strongly disagree; 7 – strongly agree) concerning the constructs together with 5 additional demographic and behavioral questions regarding: age, sex, frequency of internet usage through a mobile device, frequency of exposure to mobile advertisements through a mobile device and frequency of mobile device purchases. The measurement items regarding each construct were carefully chosen from existing literature. As noted in the literature review, past studies have explored these concepts in various ways. As such, each measurement item used in the questionnaire was picked according to the most common queries used by previous researchers.

Data was collected from consumers who own mobile devices and have experienced SMS, MMS, keyword search, display and rich media advertising through a mobile device. Before starting the survey, respondents were also presented with a message to introduce them with the content and purpose of the study as well as to guarantee their anonymity. The data collected consisted of 221 responses. Each answer was carefully scrutinized in order to make sure the data is clean and usable for further testing of validity, reliability and suitability for hypotheses testing. Out of the initial 221 responses, 13 were considered to be improper as the answers to all questions were identical. There were no missing data as the questionnaire was designed such that each question is required to be answered in order to complete the survey. The final sample size consisted of 208 responses, which fits the range of acceptable sample sizes for this research objective (Kline, 2011). Hair et al., (2010, p100) suggest a general rule to aim for a minimum of at least five times as many observations compared to the number of variables in the analysis. In the case of this research – this would mean a sample size of at least 145 observations. The final sample size is well above this minimum threshold and has a ratio of 7:1 observations to variables. The size of the sample is should be large enough in order to improve the chances of generalizability, meaning the sample is representative of the entire population.

Constructs	*Items*	*Measurement Items*	*References*
Informativeness (I)	I1 I2 I3	• Mobile advertising provides timely information on products or services. • Mobile advertising supplies relevant information on products or services. • Mobile advertising is a good source of information.	(Ducoffe, 1995; Chia-Ling et al., 2012)
Entertainment (E)	E1 E2 E3	• I feel that mobile advertising is interesting. • I feel that mobile advertising is enjoyable. • I feel that mobile advertising is entertaining	(Ducoffe, 1995; Chia-Ling et al., 2012)
Credibility (C)	C1 C2 C3	• I feel that mobile advertising is convincing. • I feel that mobile advertising is believable. • I feel that mobile advertising is credible.	(Ducoffe, 1995; Chia-Ling et al., 2012)
User Control (UC) **(Perceived Interactivity subconstruct)**	UC1 UC2 UC3	• I have control over my experience when viewing mobile advertisements • I can choose freely what I want to see when viewing mobile advertisements. • I can decide the kind of experiences I get when viewing mobile advertisements.	(Lu et al., 2019; Wu et al., 2017; Yoo et al., 2010; Tan 2018 et al.; Bao et al., 2016; Gao et al., 2010)
Two-way communication (TW) **(Perceived Interactivity subconstruct)**	TW1 TW2 TW3	• Mobile advertisements makes me feel companies want to listen to their customers • Mobile advertisements allow me to give feedback to companies • Mobile advertisements can create a conversation between companies and their customers	(Wu et al., 2017; Lu et al., 2019; Yoo et al., 2010; Gao et al., 2010; Tan et al., 2018)
Synchronicity (SN)	SN1 SN2 SN3	• I can give my response to a mobile advertisement without any delay	(Wu et al., 2017; Lu et al., 2019; Yoo et al., 2010;

(Perceived Interactivity subconstruct)		• After viewing a mobile advertisement, I can get answers fast when I request further information. • I can get instantaneous information when I respond to mobile advertisements.	Gao et al., 2010; Tan et al., 2018)
Flow experience (FE)	FE1 FE2 FE3 FE4 FE5	• When I view mobile advertisements, time seems to pass by very quickly • While I view mobile advertisements, nothing seems to matter • I am not distracted by other online activities, and stay focused on mobile advertisement • I find myself eager to press on advertising content or activity displayed on my mobile device • I like to pay attention to mobile advertisements.	(Ho & Kuo, 2010; Kim & Han 2014; Martins et al., 2019;)
Perceived Advertising Value (AV)	AV1 AV2 AV3	• I feel that mobile advertising is useful. • I feel that mobile advertising is valuable. • I feel that mobile advertising is important.	(Ducoffe, 1995; Chia-Ling et al., 2012)
Purchase Intention (PI)	PI1 PI2 PI3	• I find purchasing product/service advertised to be worthwhile. • I will frequently purchase product/service advertised in the future. • I will strongly recommend others to purchase product/service advertised.	(Hsu & Lin, 2015; Kumar, Lee, & Kim, 2009)

Table 2: Questionnaire

6. Methodology

The primary purpose of statistical techniques is to estimate the probability that the pattern of data collected could have occurred by chance rather than by the causes proposed by the theory being tested. These techniques should be carefully selected based on the type of data collected and should be carried out in the context of theory using measures derived from a theory (Lowry et al., 2014). Statistical techniques in

social sciences can be categorized as first and second generation. First generation techniques consider correlations, regression analysis, cluster analysis, exploratory factor analysis, confirmatory factor analysis or tests for differences in means such as t-tests or analysis of variance (ANOVA) (Hair et al., 2017).

These approaches are a good fit for simpler models. Correlations are convenient for exploratory research and can be employed to assess how variables are related to one another and serve as a basis for a future causal research. Tests for differences in means are particularly useful in experiments where the goal of the research is usually to establish whether the treatment condition has been influenced differently than the control condition. Typical examples include testing whether a new drug works where one group would be exposed to the treatment whereas the other group would be given a placebo and the effects would be measured over time. Regression analyses are typically fitting to simple models where the number of independent and dependent variables is low and the data is highly normalized. This method applies well to test models for moderation and mediation between the variables.

Nonetheless, these first-generation techniques are not well suited for causal or more complex models particularly when considering latent variables. Latent variables are those that cannot be directly observed but are inferred from other variables that can be measured. Examples of latent variables include concepts such as quality of life, trust, happiness etc. As an example, one could possibly measure quality of life through other variables such as wealth, physical and mental health, employment and so on. Additionally, first generation techniques are not a good fit to explore multiple group moderation of multiple effects, multiple group moderation of multiple effects, and assessing the "goodness" of the proposed (tested) model in comparison with the observed relationships contained in the data (Lowry et al., 2014). This research employs an independent samples t-test to evaluate whether there exists a difference between attitudes towards mobile advertising when controlling for gender. The software used for this purpose was IBM SPSS Statistics v26.

Second generation techniques such as structured equation modeling (SEM) are statistical methods that are better suited for causal networks of effects at the same time. One of the advantages of SEM is the capacity to incorporate latent variables in a causal

model. This allows researchers to model different constructs composed of various indicators and evaluate the complete causal network simultaneously. SEM includes a diverse collection of statistical techniques including: confirmatory factor analysis, confirmatory composite analysis, path analysis, partial least squares path modeling, and latent growth modeling (Kline, 2011). SEM has changed the nature of research in international marketing and management. It is a statistical technique for testing and estimating causal relationships using a combination of statistical data and qualitative causal assumptions (Martins et al., 2019). There are two types of SEM: covariance based representing constructs as factors (CB-SEM) & least squares based that represents constructs through components (PLS). PLS incorporates several statistical techniques that are not part of CB-SEM—such as principal components analysis, multiple regression, multivariate analysis of variance, redundancy analysis, and canonical correlation —without inflating the t-statistic, as would happen if each analysis were conducted separately from the others (Lowry et al., 2014). PLS is particularly well suited when it comes to exploratory research when testing new models is the primary goal of the researcher. Covariance-based SEM is a better fit when the goal is to evaluate whether a model that already exists in the literature would yield consistent results. Additionally, CB-SEM is advantageous in assessing overall model fit of the conceptual causal model. Although the latent variables and their corresponding relationships proposed in the conceptual model in this research stems from a large body of literature in web and mobile advertising, I could not find another study that had employed the same exact model. Thus, the use of PLS-SEM fits the research objective more strongly than CB-SEM. The software used for this purpose was SmartPLS (v.3.2.9).

7. Descriptive Statistics

As shown in the table 3 below, the final sample consists of 208 individuals, which fully completed the questionnaire. In terms of sex, the sample is consistent with roughly the same proportion of male to female (51% vs. 49%). Considering age, most of the participants who completed the survey fall within the 20-29 years category (72%), followed by younger participants who were under 20 years (13%) and respondents in the 30-39 age group (11%). Nearly half of the respondents were

employed, while more than a third were students. The vast majority surf the internet through a mobile device for at least 2 hours a day and consume at least one advertisement on a daily basis.

Measure	***Item***	***N***	***Percentage (%)***
Sex	Male	106	51%
	Female	102	49%
Age	Under 20	26	13%
	20-29	149	72%
	30-39	23	11%
	40-49	7	3%
	50-59	3	1%
Employment Status	Unemployed	18	9%
	Student	82	39%
	Employed	93	45%
	Doctorate	4	2%
	Self-Employed	7	3%
	Freelancer	4	2%
Internet usage period (via mobile device)	Under 1 hour	7	3%
	1h – 2h	41	20%
	2h – 3h	65	31%
	Over 3h	95	46%
Frequency of viewing an advertisement on mobile device	Seldom	56	27%
	1 – 3 per day	91	44%
	>3 per day	61	29%

Last purchase of a mobile device	Under 6 months	55	26%
	6 months – 1 year	50	24%
	1 year – 2 years	60	29%
	2 years – 3 years	31	15%
	Over 3 years	12	6%

Table 3: Descriptive Statistics

8. General attitude towards mobile advertising

This section explores the dataset collected for any general attitudes towards mobile advertising. Taking a look at the mean score for each measurement item, one can observe that the minimum average score is 2,3606 whereas the maximum is 3,4712. As respondents had to evaluate each statement on a 7-point Likert scale where 1 stands for strongly disagree, 4 – neither disagree nor agree and 7 - strongly agree, we can observe a general trend of a negative attitude towards mobile advertising. None of the questions scored an average score that is higher than 4. Since all questions posed are designed to assess perceptions on advertising in a positive fashion, participants seem to largely disagree on the overall value they receive via mobile ads. This trend seems to persist even when controlling for gender. Using IBM SPSS Statistics v26, there were no significant differences in means (p value <0,05) between males and females found by running an independent samples t-test as the results show in table 4 below.

Measurement Item	***Minimum***	***Maximum***	***Mean***	***Std. Deviation***	***t-test (2-tailed) sig. (Gender)***	***Mean Difference (Gender)***
I1	1,00	7,00	2,4663	1,24676	0,962	-,00832)
I2	1,00	7,00	2,9904	,91678	0,364	0,1158
I3	1,00	7,00	2,9760	1,01410	0,629	0,06826
E1	1,00	7,00	2,6154	1,17385	0,149	-,23529)

E2	1,00	7,00	2,3606	1,17123	0,927	0,01498
E3	1,00	7,00	3,0865	,84683	0,977	-,00333)
C1	1,00	7,00	2,7115	1,33459	0,723	-,06585)
C2	1,00	7,00	3,6683	,96336	0,867	0,02238
C3	1,00	7,00	2,6202	1,26452	0,849	-,03348)
UC1	1,00	7,00	2,6875	1,08278	0,129	-,22845)
UC2	1,00	7,00	2,2837	1,18824	0,159	-,23215)
UC3	1,00	7,00	2,9279	1,30016	0,374	-,16075)
TW1	1,00	7,00	2,6202	1,27214	0,978	0,00499
TW2	1,00	7,00	2,5337	1,28868	0,56	0,10451
TW3	1,00	7,00	2,6538	,98068	0,704	0,05179
SN1	1,00	7,00	2,7644	1,01071	0,491	-,09674)
SN2	1,00	7,00	3,3077	1,24781	0,463	-,12727)
SN3	1,00	7,00	3,4712	1,11604	0,39	-,13356)
AV1	1,00	7,00	2,7452	1,14524	0,069	-,28838)
AV2	1,00	7,00	2,7212	1,12036	0,096	-,25860)
AV3	1,00	7,00	3,2788	1,38980	0,177	-,26082)
PI1	1,00	7,00	2,4423	1,23027	0,318	-,17092)
PI2	1,00	7,00	2,5913	1,11698	0,649	-,07085)
PI3	1,00	7,00	3,2115	1,03254	0,259	-,16204)
FE1	1,00	7,00	2,6394	1,18761	0,796	0,04273
FE2	1,00	7,00	2,5192	1,28898	0,833	0,03774
FE3	1,00	7,00	2,9183	,93150	0,729	-,04495)
FE4	1,00	7,00	3,1635	,98893	0,225	0,16685
FE5	1,00	7,00	3,2692	,97536	0,285	-,14502)

Table 4: Mean Scores & Gender Difference

9. Data Screening, Validity & Reliability

a) Missing Data, Unengaged Responses, Outliers

As the questionnaire was designed in a particular way where one cannot submit their responses without answering all questions, there was no missing data. Additionally, all queries related to constructs were measured on a 7-point likert scale and as such there were no outliers in the dataset. If a respondent had chosen the same answer to every question, it was considered an unengaged response. Out of the 221 responses collected, 13 were considered unengaged responses and were omitted from the dataset.

b) Skewness & Kurtosis

PLS-SEM is a nonparametric statistical technique that does not require data to follow a normal distribution. However, it is still important to evaluate whether the data is not too far from a normal distribution as nonnormal data could inflate standard errors obtained through bootstrapping. Skewness assesses the extent to which a variable's distribution is symmetrical. If the distribution of responses for a variable stretches toward the right or left tail of the distribution, then the distribution is referred to as skewed. Kurtosis is a measure of whether the distribution is too peaked (a very narrow distribution with most of the responses in the center)." (Hair et al., 2017, p. 61). In a set of data that follows a perfect normal distribution, the values of skewness and kurtosis are 0. According to Hair et al. (2017), a value higher than +1 or lower than -1 is an indication for a substantially skewed distribution. Similarly, values higher than +1 for kurtosis could indicate that the distribution is too peaked, whereas values lower than -1 that the distribution is too flat. As shown in figure 7 below, the data collected exhibits skewness values that at most are close to +1 in the majority of cases, which can be considered as proper. This is not the case for the following variables: TW3 (skewness 1,3) & AV2 (skewness 1,255). Similarly, when assessing kurtosis in the distribution, most variables fit within the range of +1 and -1. However, one can detect potential kurtosis issues with the following variables: E3 (3,131); TW3 (2,214); AV2 (1,631); F3 (1,367); I1 (1,404); I2 (1,427). Although there are 6 variables that seem to

deviate from the +1 to -1 guideline proposed above, other researchers suggest a more liberal approach to data distribution when utilizing SEM: -3 to +3 for skewness & -10 to +10 for kurtosis (Brown, 2006). Additionally, Hair et al., (2017) also agree that while lack of normality of variable distributions can distort the results of multivariate analysis - this problem is much less severe with PLS-SEM. Since the dataset used for the purpose of this research fits well within this range, it is deemed acceptable and can continue to be used for further analyses. Table 5 presents the values of skewness & kurtosis for all variables.

	I1	**I2**	**I3**	**E1**	**E2**	**E3**
Skewness	1,112	,855	,582	1,058	1,069	1,039
Kurtosis	1,404	1,427	,549	1,069	1,201	3,131
	C1	**C2**	**C3**	**UC1**	**UC2**	**UC3**
Skewness	,677	,675	,573	,949	1,022	,601
Kurtosis	-,082)	,408	-,198)	1,151	,957	,336
	TW1	**TW2**	**TW3**	**SN1**	**SN2**	**SN3**
Skewness	,915	,951	1,300	1,253	,619	,041
Kurtosis	,574	,657	2,214	1,787	,570	,418
	AV1	**AV2**	**AV3**	**PI1**	**PI2**	**PI3**
Skewness	,981	1,255	,580	1,022	1,007	,709
Kurtosis	,790	1,631	,177	,932	1,118	1,152
	FE1	**F2**	**F3**			
Skewness	,747	,914	,924			
Kurtosis	,470	,486	1,367			
Std. Error of Skewness	,169					
Std. Error of Kurtosis	,336					

Table 5: Skewness & Kurtosis

c) Measurement Model: Convergent Validity & Reliability of Indicators

In order to assess the results of the measurement model, this section focuses on establishing convergent validity (individual indicator reliability & average variance extracted), internal consistency and discriminant validity.

Internal consistency is a measure that allows researchers to assess whether the multiple measurement items, which are supposed to measure the same construct, really do in fact seem to measure what was intended. The traditional criterion for internal consistency is Cronbach's alpha (CA), which provides an estimate of the reliability based on the intercorrelations of the observed indicator variables (Hair et al., 2017). A value of Cronbach Alpha that is higher than 0,7 is deemed acceptable in the research world to suggest scale reliability. As shown in the figure 7 below, all constructs have a CA value of at least 0,8, which satisfies the above-mentioned condition. In order to further gauge internal consistency reliability, researchers can also use composite reliability – which considers different outer loadings. Values of composite reliability (CR) between 0,6 to 0,9 are deemed acceptable and each factor in this study is well within this range. Values above 0,9 of both CA & CR are considered undesirable as they point to measurement items assessing the same concept – researchers are advised to minimize the number of redundant factors.

Convergent validity is the extent to which a measurement item is positively correlated to other measures of the same construct. As this is a reflective model, items are expected to be highly correlated with one another when measuring the same construct. In order to evaluate convergent validity, I take a look at the factor loadings and the average variance extracted (AVE). Values of at least 0,5 can be considered acceptable for factor loadings whereas researchers should aim for values above 0,708 (Hair et al., 2010). The initial principal component analysis showed acceptable scores of factor loadings for all variables except for the measurement items FE4 & FE5 for the Flow Experience construct, As the loadings for these factors were below 0,5 respectively (0,492 & 0,476), they were dropped from the analysis. The remaining model consisted of 27 variables and showed factor loadings of >0,7 for 25 items and >0,5 for 2 items (I3 = 0,668; PI3 = 0,516).

All the constructs have loadings higher than 0,5 except for Perceived Interactivity as it's a second order construct. I have established the convergent validity (loadings & AVE), internal consistency reliability (CA & CR). FE4 & FE5 were dropped due to a low factor loading (<0,5). Average Variance Extracted is a common method to establish convergent validity on a construct level. An AVE value higher than 0,5 points suggests that, on average, the construct explains more than half of the variance of its indicators. Conversely, an AVE of less than 0,5 indicates, that on average, more variance remains in the error of the items that in the variance explained by the construct (Hair et al., 2017). All of the constructs hold AVE values of above 0,5 and thus construct convergent validity is satisfied. Table 6 presents the factor loadings, composite reliabilities, Cronbach Alpha values and average variance explained.

Constructs	***Loadings***	***CR***	***CA***	***AVE***
Informativeness		0.883	0.877	0.725
I1	1.082			
I2	0.746			
I3	0.668			
Entertainment		0.842	0.836	0.641
E1	0.865			
E2	0.823			
E3	0.705			
Credibility		0.865	0.866	0.682
C1	0.849			
C2	0.826			
C3	0.801			
User Control		0.863	0.863	0.677
UC1	0.887			
UC2	0.802			

UC3	0.776			
Two-way com.		0.887	0.874	0.705
TW1	0,916			
TW2	0.808			
TW3	0.789			
Synchronicity		0.840	0.841	0.639
SN1	0.883			
SN2	0.797			
SN3	0.708			
P. Interactivity		0,837	0,836	0,769
UC	0,843			
TW	0,882			
SN	0,904			
P. Ad Value		0.884	0.883	0.717
AV1	0.880			
AV2	0.850			
AV3	0.809			
Flow Experience		0.9	0.896	0.751
FE1	0.971			
FE2	0.827			
FE3	0.790			
P. Intention		0.830	0.825	0.633
PI1	0.920			
PI2	0.886			
PI3	0.516			

Table 6: Factor Loadings, Composite Reliabilities, Cronbach Alpha, Average Variance Explained

d) Discriminant Validity

Discriminant validity evaluates how well a construct is truly distinct from other constructs. Establishing discriminant validity shows that constructs are unique and are measuring phenomena different than the other constructs. In order to assess discriminant validity, I take a look at three criteria: Cross-loadings, Heterotrait-Monotrait Ratio & Fornell-Lacker criterion. Cross-loadings analysis includes exploring whether the outer loading on a specific construct is higher than any of its correlations to the other constructs. As can be seen in table 7 below, the outer loadings of items on the construct they are supposed to measure are higher than any of their correlations with the other constructs (values in bold vs. values not in bold).

	C	**E**	**FE**	**I**	**AV**	**PInter**	**PI**	**SN**	**TW**	**UC**
AV1	0.449	0.498	0.346	0.445	**0.876**	0.550	0.346	0.379	0.431	0.403
AV2	0.439	0.484	0.320	0.426	**0.844**	0.438	0.341	0.312	0.335	0.320
AV3	0.425	0.390	0.352	0.417	**0.819**	0.461	0.344	0.400	0.275	0.348
C1	**0.849**	0.433	0.449	0.500	0.439	0.524	0.345	0.412	0.339	0.409
C2	**0.826**	0.371	0.222	0.364	0.427	0.398	0.207	0.348	0.317	0.210
C3	**0.801**	0.330	0.164	0.336	0.414	0.323	0.200	0.292	0.279	0.135
E1	0.440	**0.865**	0.472	0.454	0.468	0.587	0.354	0.451	0.442	0.399
E2	0.409	**0.823**	0.368	0.476	0.445	0.642	0.387	0.508	0.443	0.468
E3	0.235	**0.705**	0.275	0.318	0.382	0.414	0.261	0.272	0.418	0.216
F2	0.320	0.433	**0.823**	0.423	0.339	0.494	0.442	0.356	0.415	0.315
F3	0.185	0.335	**0.817**	0.369	0.237	0.503	0.455	0.363	0.339	0.410
FE1	0.369	0.449	**0.947**	0.447	0.450	0.564	0.497	0.425	0.426	0.393
I1	0.508	0.528	0.410	**1.082**	0.549	0.580	0.454	0.409	0.411	0.462
I2	0.417	0.443	0.444	**0.747**	0.379	0.536	0.383	0.415	0.410	0.355
I3	0.296	0.357	0.397	**0.668**	0.339	0.409	0.298	0.361	0.247	0.297

PI1	0.343	0.401	0.475	0.429	0.399	0.536	**0.912**	0.430	0.430	0.318
PI2	0.194	0.281	0.476	0.388	0.360	0.491	**0.886**	0.331	0.431	0.316
PI3	0.177	0.345	0.311	0.220	0.164	0.360	**0.529**	0.237	0.344	0.208
SN1	0.402	0.571	0.415	0.461	0.398	0.798	0.414	**0.883**	0.435	0.404
SN1	0.402	0.571	0.415	0.461	0.398	0.677	0.414	**0.930**	0.435	0.404
SN2	0.324	0.379	0.314	0.307	0.357	0.721	0.339	**0.797**	0.340	0.265
SN2	0.324	0.379	0.314	0.307	0.357	0.600	0.339	**0.998**	0.340	0.265
SN3	0.287	0.269	0.326	0.316	0.264	0.640	0.260	**0.708**	0.254	0.266
SN3	0.287	0.269	0.326	0.316	0.264	0.544	0.260	**0.905**	0.254	0.266
TW1	0.385	0.542	0.474	0.433	0.432	0.807	0.499	0.431	**0.916**	0.328
TW1	0.385	0.542	0.474	0.433	0.432	0.689	0.499	0.431	**0.992**	0.328
TW2	0.335	0.446	0.398	0.386	0.320	0.712	0.441	0.382	**0.808**	0.216
TW2	0.335	0.446	0.398	0.386	0.320	0.602	0.441	0.382	**0.942**	0.216
TW3	0.224	0.367	0.263	0.230	0.274	0.696	0.320	0.277	**0.789**	0.315
TW3	0.224	0.367	0.263	0.230	0.274	0.560	0.320	0.277	**0.921**	0.315
UC1	0.375	0.465	0.396	0.478	0.463	0.748	0.365	0.389	0.349	**0.887**
UC1	0.375	0.465	0.396	0.478	0.463	0.632	0.365	0.389	0.349	**0.936**
UC2	0.178	0.324	0.321	0.290	0.332	0.676	0.264	0.275	0.250	**0.802**
UC2	0.178	0.324	0.321	0.290	0.332	0.562	0.264	0.275	0.250	**0.995**
UC3	0.193	0.336	0.344	0.315	0.233	0.654	0.249	0.305	0.240	**0.776**
UC3	0.193	0.336	0.344	0.315	0.233	0.552	0.249	0.305	0.240	**0.924**

Table 7: Cross-loadings Analysis

Heterotrait-Monotrait Ratio (HTMT) is the average of the heterotrait-heteromethod correlations (i.e., the correlations of indicators across constructs measuring different phenomena), relative to the average of the monotrait-heteromethod correlations (i.e., the correlations of indicators within the same construct), which takes the geometric

mean of their average correlations (Henseler et al., 2015). The HTMT approach technically estimates what would be the true correlation of two constructs were they to be measured perfectly. Henseler et al., (2015) suggest a threshold value of less than 0,9 to establish discriminant validity via HTMT. All constructs are well below this threshold value as can be seen in table 8 below.

	C	E	FE	I	AV	Inter	PI	SN	TW	UC
Credibility										
Entertainment	0.454									
Flow Experience	0.335	0.469								
Informativenes	0.483	0.528	0.498							
P. Ad Value	0.517	0.543	0.397	0.504						
P. Interactivity	0.497	0.683	0.602	0.602	0.567					
P. Intention	0.303	0.439	0.540	0.443	0.394	0.586				
Synchronicity	0.421	0.506	0.441	0.467	0.426		0.420			
Two-way Com.	0.376	0.546	0.453	0.422	0.407		0.513	0.428		
User Control	0.299	0.451	0.431	0.438	0.416		0.356	0.388	0.340	

Table 8: Heterotrait-Monotrait Ratio

In order to further assess discriminant validity, I take a look at the Fornell-Lacker criterion. This measure compares the square root of AVE with the construct correlations – the goal being the square root of each construct's AVE should be higher than its highest correlation with another construct. In other words, a construct shares more variance with its measurement items than with any other construct. Table 9 below shows the values and further supports the establishment of discriminant validity since they all satisfy the previously mentioned condition.

	C	E	FE	I	AV	PI	SN	TW	UC
Credibility	0.826								
Entertainment	0.459	0.801							

Flow Experience	0.341	0.470	0.866						
Informativeness	0.486	0.525	0.478	0.851					
P. Ad Value	0.517	0.541	0.401	0.507	0.847				
P. Interactivity	0.505	0.691	0.601	0.598	0.572				
P. Intention	0.305	0.420	0.536	0.449	0.406	0.796			
Synchronicity	0.426	0.520	0.441	0.457	0.429	0.427	0.799		
Two-way Com.	0.378	0.542	0.455	0.421	0.412	0.503	0.436	0.839	
User Control	0.308	0.459	0.429	0.443	0.422	0.358	0.395	0.342	0.823

Table 9: Fornell-Lacker Criterion

10. Structural Model Assessment

In order to assess the structural model, I take a look at the existence of any multicollinearity issues, significant effects of the structural model relationships, level of R^2 and predictive relevance Q^2.

a) Multicollinearity (VIF values)

In order to assess the degree of multicollinearity in the structural model, I look into the variance inflation factor measure (VIF). VIF is defined as the reciprocal value of tolerance. Tolerance measures the amount of variance of one construct not explained by the other constructs in the same block. The threshold for VIF is a value less than 5 in order to establish there are no multicollinearity issues in the model. If a value of VIF is too high, for example 5, that suggests that the remaining constructs account for 80% of the variance of the associated factor. Table 10 below presents the VIF values for each construct and suggest that there are no multicollinearity problems as no VIF value is higher than 5.

	FE	***AV***	***PInter***	***PI***	***SN***	***TW***	***UC***
Credibility		1.417					
Entertainment		1,492					
Flow Experience				1.192			
Informativeness		1.542					
Perceived Advertising Value	1.485			1.192			
Perceived Interactivity	1.485				1.000	1.000	1.000

Table 10: Inner VIF Values

b) Results

PLS-SEM uses a nonparametric procedure for statistical tests called the bootstrapped procedure. The bootstrap method allows for testing to estimate the statistical

significance of path coefficients. A large number of samples are drawn from the original sample with replacement. Replacement means that each time an observation is drawn at random from the sampling population, it is returned to the sampling population before the next observation is drawn (i.e., the population from which the observations are drawn always contains all the same elements). Therefore, an observation for any bootstrap sample can be selected more than once or may not be selected at all for the sample (Hair et al., 2017). Bootstrapping samples are employed for the estimation of the path model. For example, if 2000 bootstrapped samples are chosen, 2000 PLS path models will be estimated. These estimates (coefficients) form a distribution that allows for statistical testing of the original sample on the basis of the standard deviation and standard errors of the bootstrapped coefficients. Consistent PLS bootstrapping algorithm within SmartPLS software was used for this procedure. The confidence interval method used was bias-corrected and accelerated (BCa) bootstrap. The test type was two tailed and 5000 subsamples were created. The results are discussed underneath.

First, flow experience is positively and significantly affected by interactivity (β = 0,555; p<0,01). These findings suggest that feeling in control when consuming the advertisement coupled with the ability to instantly communicate and receive feedback from the advertiser induce the flow experience. Thus, H1 is supported. Second, purchase intention is positively associated with flow experience (β = 0,447; p < 0,01). Thus, H2 is supported. The more consumers are concentrated on the advertisement, lose track of time and feel more likely to interact with the advertisement, the higher the probability that they intent to make a purchase. Third, informativeness (β = 0,216;p < 0,05), entertainment (β = 0,302; p <0,01) and credibility (β = 0,273; p<0,05) are positively associated with perceived advertising value. Thus, H3a, H3b and H3c are supported. When advertisements are seen as credible, provide consumers with proper information and engage them, consumers get higher value out of thme. Fourth, purchase intention is positively impacted by perceived advertising value (β = 0,227; p < 0,05). Thus, H4 is supported – when consumers get higher value out of the advertisement, they are more likely to make a buying decision. Finally, the impact on perceived advertising value by flow experience was found to be insignificant (β = 0,083; p > 0,1). Thus, H5 is not supported. This finding suggests that valuing the

advertisement does not necessarily induce flow. A summary of all the hypotheses test results is shown in Table 11.

Hypotheses	Independent Variables	Dependent Variables	Findings	Results
H1	Perceived Interactivity	Flow Experience	Positive and statistically significant (β = 0,555; p<0,01)	Supported
H2	Flow Experience	Purchase Intention	Positive and statistically significant (β = 0,447; p < 0,01)	Supported
H3a	Informativeness	Perceived Advertising Value	Positive and statistically significant (β = 0,216;p < 0,05)	Supported
H3b	Entertainment	Perceived Advertising Value	Positive and statistically significant (β = 0,302; p <0,01)	Supported
H3c	Credibility	Perceived Advertising Value	Positive and statistically significant (β = 0,273; p<0,05)	Supported
H4	Perceived Advertising Value	Purchase Intention	Positive and statistically significant (β = 0,227; p < 0,05)	Supported
H5	Perceived Advertising Value	Flow Experience	Non-significant effect (β = 0,083; p > 0,1)	Not supported

Table 11: Hypotheses Conclusions

c) Coefficient of Determination R^2

To assess the structural model's predictive power, the coefficient of determination (R^2) is used. This coefficient ranges from 0 to 1, with values closer to 1 indicating stronger levels of predictiveness. This coefficient is a measure of the model's predictive power and is calculated as the squared correlation between a specific endogenous construct's actual and predicted values. The coefficient represents the exogenous latent variables' combined effects on the endogenous latent variable (Hair et al., 2017). In marketing research, a general rule of thumb is that R^2 values of 0,75, 0,50 or 0,25 for endogenous constructs are considered substantial, moderate or weak (Henseler et al., 2009). However, one potential flaw of R^2 is that by increasing the exogenous constructs always increases the R^2 value. To contrast this, the adjusted coefficient of determination R^2_{adj} takes into consideration the number of exogenous constructs compared to the sample size in order to correct for the previously mentioned bias. Table 12 below presents the results of R^2 & R^2_{adj} as well as the corresponding p values, which are all less than 0,001.

	R^2	R^2_{adj}	Standard Deviation	P Values R^2	P Values R^2_{adj}
Flow Experience	0.368	0.362	0.082	0.000	0.000
Perceived Advertising Value	0.415	0.406	0.074	0.000	0.000
Purchase Intention	0.332	0.326	0.071	0.000	0.000

Table 12: Coefficient of Determination & Adjusted Coefficient of Determination

According to the scores presented in the table, the research explains 36,8% of the variation in flow experience in the conceptual model. The model explains 41,5% of variance in Perceived Advertising Value and 33,2% of variance in Purchase Intention. Taking into account the nature of the research, these values can be considered as moderate effects. The figure below presents the overall results of the structural model including the path coefficients, respective t-values and the coefficient of determination in the endogenous latent variables.

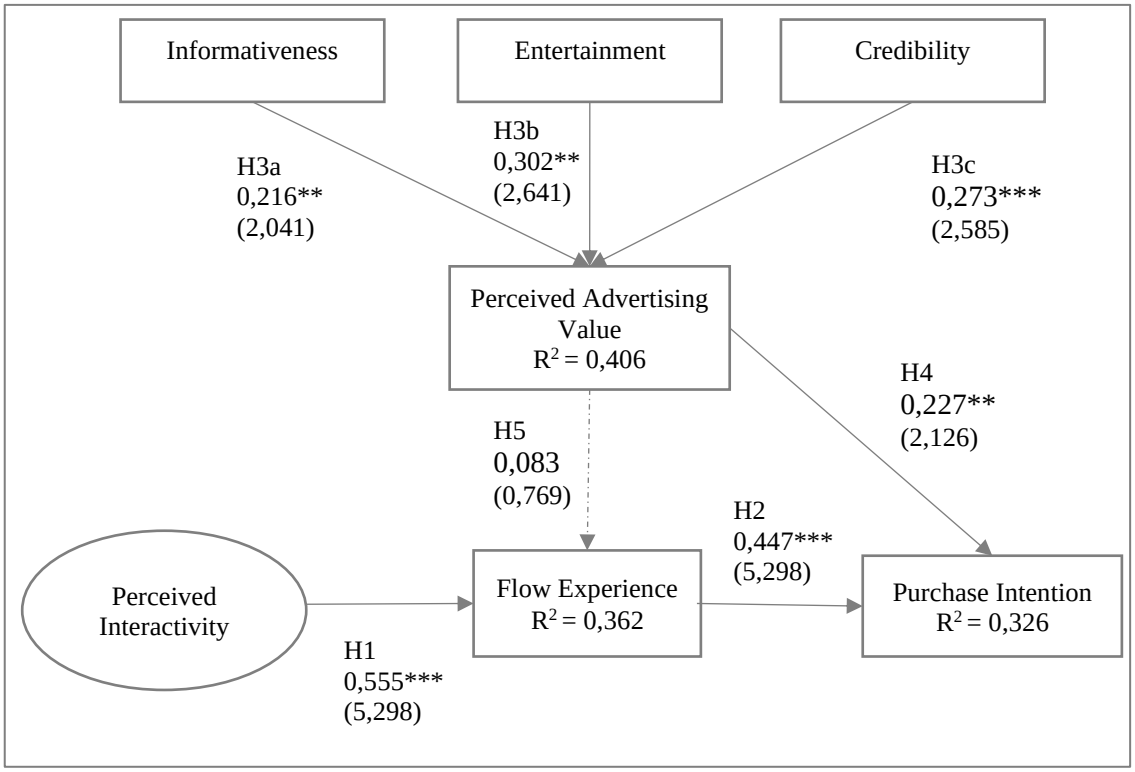

Figure 3: Structural Model results

d) Predictive Relevance - Blindfolding (Q^2)

In addition to the size of R^2, the predictive sample reuse technique (Q^2) can effectively be used as a criterion for predictive relevance. Based on blindfolding procedure, Q^2 evaluates the predictive validity of a large complex model using PLS (Akter et al., 2011). The PLS adaptation of this approach follows a blindfolding procedure that omits a part of the data for a particular block of indicators during parameter estimations and then attempts to estimate the omitted part using the estimated parameters (Chin, 2010). Thus, Q^2 measures the extent to which observed values are reconstructed by the model. Values of Q^2 higher than 0 indicate that the model has predictive qualities, while values of Q^2 lower than 0 represent a lack of predictive relevance. The Q2 value can be obtained via two different approaches: cross-validated redundancy approach & cross-validated communality approach. Hair et al., (2017) suggest the use of cross-validated redundancy approach as it includes the structural model to predict eliminated data points, which fits the PLS-SEM approach perfectly. Running the blindfolding algorithm in SmartPLS using an omission distance equal to 7 produced the results shown in table 13 below. This finding suggests that the model has predictive quality as $Q^2 > 0$ for all 3 endogenous latent variables.

	SSO	SSE	Q^2 (=1-SSE/SSO)
Flow Experience	624.000	478.845	0.233
Perceived Advertising Value	624.000	464.115	0.256
Purchase Intention	624.000	506.711	0.188

Table 13: Construct Cross-validated Redundancy

11. Discussion

The purpose of the study was to understand the impact of consumers' perceived interactivity, flow experience & perceived advertising value when consuming mobile advertisements on their purchase intention. The empirical findings were: first, perceived interactivity seems to be a catalyst to flow experience. The phenomenon of feeling in control together with being able to instantly communicate back and forth with the advertiser helps consumers enter a flow state. Second, flow experience positively impacts purchase intention. When consumers are experiencing flow, they are more likely to make a purchase. Thus, it is important to consider the importance of interactivity when creating advertisements. Third, entertainment, informativeness and credibility are predictors of perceived advertising value. Advertisements have to be seen as believable and inspire trust in consumers, provide the right information and be engaging in order for consumers to consider them valuable. Fourth, advertising value positively impacts purchase intention. If consumers find the advertising valuable, they are more likely to engage in the buying process. Finally, advertising value did not significantly predict flow experience. This finding suggests that even though flow and advertising value both lead to an increase in purchase intention, there seem to be other potential factors that could explain purchase intention. In other words, just because an advertisement is deemed valuable does not necessarily mean it helps induce a flow state. Nevertheless, it should still be considered that flow experience is not completely a prerequisite to make a purchase. However, according to these findings, the relative importance of flow seems to be higher than advertising value as indicated by the model.

This research has several theoretical implications. First, it contributes to bridge the gap in investigating antecedents to flow in the mobile environment. The results indicate that interactivity aids in facilitating flow and is consistent with previous studies (Ho et al., 2010; Wu et al., 2005). Second, Ducoffe's web advertising model is confirmed in the mobile context. The findings are very consistent with the existing literature (Martins et al., 2019; Wu et al., 2017; Dao et al., 2014; Bevan-Dye et al., 2013). Entertainment was the strongest positive factor, followed by credibility and informativeness. One reason for this could be consumers value being engaged more

highly in a mobile context due to the generally higher number of distractions on a mobile screen. Thus, catching their attention seems to contribute the highest to value. Nevertheless, believing in the advertisement content and feeling properly informed are still important factors to consider. Third, experiencing flow and deriving value from advertisements can both lead to a higher intent to purchase a product or service. Once more as these findings are consistent with previous literature, this contributes the advertising fields by exploring these results in a mobile context (Kim et al., 2014). Fourth, as advertising value failed to predict flow, this represents an opportunity for research to examine it in other settings or different cohorts. This finding is contradictory to previous research and further investigation should be warranted to better understand these two concepts (Martins et al., 2019).

Several practical implications can also be drawn. First, advertisers on mobile devices should consider all concepts included in this study as each one of them contributed to consumers' purchase intention. Practitioners should also keep in mind to choose settings or platforms where these concepts could be more easily utilized. In terms of facilitating flow, this study shows the importance of making sure the user feels in control and can instantly send and receive feedback from the advertiser. For example, if the goal is to induce a purchase for a service that consumers would typically have further questions, a banner ad might be less effective than a Facebook advertisement, which allows for immediate communication either through the comment section of the advertisement or directly through the Facebook page of the advertiser. Additionally, marketers should focus on creating engaging and informative content, while making sure to also establish social proof from a brand point of view. Most of the platforms typically allow for ad sets that necessarily show what company stands behind the ad and thus would be advisable to invest in attractive solutions to meet consumers' expectations from a branding standpoint.

12. Limitations and future research

This study has several limitations that need to be considered. First, online surveys are a form of convenience (non-probability) sampling and as such are prone to self-selection bias, which could pose a potential danger for generalizability. Additionally, despite there being an equal split in terms of gender, it is important to note that the

large majority of the respondents of the survey were in the 20-29 age group (72%), which is not representative of society at large. Moreover, 39% of respondents described themselves as students, which presents another bias in the sample. Finally, while the survey was conducted online and respondents were from various regions in the world, a significant portion of respondents were from North Macedonia (home country of author).

The research design followed a cross-sectional study, so this could be a limiting factor given the how fast mobile-based advertising is evolving. Further research that investigates the effect of advertising value on flow experience is welcome as this finding was inconsistent with previous research and it would be good to see whether this finding would persist in other settings. In addition, this study focused on perceptions towards mobile advertisements in general and did not show specific types of mobile advertisements. Although there are findings that suggest congruency of results between general perceptions and specific ad experiments (Ducoffe, 1996), it is not a topic that has been rigorously investigated. Mobile advertising comes in many different forms and future research could focus on investigating these concepts on a specific platform such as Facebook or Google.

One can also consider other measures as the ultimate goal for advertising besides purchase intention, such as attitude towards advertisement or behavioral measures (clickthrough rate or conversion rates). Additionally, the constructs estimated in the model represent only a part of what researchers have already investigated when exploring drivers of purchase intention. There are many other concepts that have been employed and have shown explanatory power such as perceived usefulness, perceived easy of use, irritation, incentives, brand awareness etc. However, this was beyond the scope of this study.

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