PROGRAMMATIC ADVERTISING AND CONSUMER ATTITUDES IN ONLINE RETAILING

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ABSTRACT

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Abstract

Programmatic advertising (PA) has gained its popularity in the field of marketing. According to the literature review, there has been various studies about PA's characteristics and exploring PA from business's perspective. Research has also created a link between the PA and metaverse since metaverse has largely been considered as a new digital advertising channel and medium through which brands can connect with customers. However, there are dearth studies about PA's effect on consumers. Therefore, this study aims to contribute to the aforementioned research gap so that consumer's perspective about PA-empowered ads can be brought to light and how it leads to their correspondent behaviours such as intention to purchase and ad avoidance.

Driven by the TRA and SOR theories, this thesis studies the effect of PA-empowered ads on customer attitude in the context of online retailing. Quantitative methodology using a pre-tested survey owing to its effectiveness in proving causal relationships between variables and it has been widely applied in consumer behaviours and attitudes studies, was used to collect the data during March 2023. Research data is collected via online survey due to its budget and time effectiveness. Perceived relevance, timeliness, and intrusiveness are chosen as triggering elements towards consumer attitudes, which leads to their behaviour performance of intention to purchase and avoidance ads.

The findings reveal that perceived relevant and timeliness have significantly positive relationships with consumer attitude towards the ads. In contrast, when consumers perceived the ads as intrusive, they develop a negative impression towards the ads. Positive attitude about the ads will increase consumers' intention to purchase the advertised product or service whilst negative consumer attitude will increase their avoidance towards the ads. These results confirm and support previous studies in the context of PA and online retailing. More importantly, the scope of this study justifies that consumer attitudes have direct and positive impact on ad avoidance, which has not been observed in prior studies.

Key words
Programmatic advertising, consumer attitudes, purchase intention, ad avoidance

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1 INTRODUCTION

This chapter introduces four main parts of the study including the study's background, its objective and research questions, the study's structure, and the related key terms. In study background, the selected topics will be briefly represented regarding its core concept, theory, its relation to online retail, and its theorical development. Following that, the purposes and research questions of this study are explained. Thirdly, the structure of this study is introduced in detail. As there are various key concepts and terms appearing throughout the study, a list of selected terms is composed.

1.1 Study background

In this section, a general background introduction about programmatic advertising is represented prior to introducing its position in the context of online retailing landscape. After that, two theoretical frameworks are mentioned.

1.1.1 Programmatic advertising

Programmatic advertising applies computational advertising approach to enhance marketing effectiveness so that ad buyers can directly purchase ad exposures through automated online auction in real-time ad exchange market (Malthouse et al., 2018). Due to their effectiveness, ads empowered by programmatic technology have been widely used by ad buyers. Therefore, this study explores the effect of ads as a product of programmatic advertising (PA hereinafter) on consumers' attitudes, which has a direct impact on their purchase intention and their avoidance behaviors towards the ads.

Previous studies regarding programmatic advertising mainly focused on exploring its characteristics (Bang et al., 2018; Busch, 2016; Chen et al., 2019; Li et al., 2017; Malthouse et al., 2018; Paulson et al., 2018; Shehu et al., 2021). Later on, other studies explored PA as an application of internet behavior for serving relevant television ads (Bellman et al., 2013), or as a future of display ads in the Internet Advertising Paid Slot (Aslam & Karjaluoto, 2017), to name a few. However, there is dearth studies exploring consumer's attitudes and its dependent elements towards PA practice (Ciuchita et al., 2022; Samuel et al., 2021; Zhang et al., 2020). Hence, this study aims to contribute to the exploration of consumer's perspective toward the application of PA in the context of online retailing. Particularly it focuses on how consumer online shopping intention and ad avoidance behavior are affected after seeing the displayed ads employed by PA technologies.

According to the Interactive Advertising Bureau (IAB herein) report on year 2023 (p.6), digital advertising revenue for the first time totalling over 200 billion US dollars despite all the economic constrains. Among which, programmatic advertising revenue was 109.4 billion US dollars with an increase of 10.5% year over year growth. The programmatic advertising spending is forecasted to grow with a compound annual growth rate of 26.6% from 2021 to 2026 (Technavio, n.d.). Conversely, as the digital advertising market becomes more unstable with changes in legislation, and content modification, 50% of marketers feel negative about the growth of programmatic ad spending in 2023 (*Bad News for Publishers*, n.d.). Meanwhile, forecast on US digital ad spending from 2022 to 2024 has been adjusted to 5.51 billion lower compared to previous prediction (*Digital Advertising Trends to Watch for 2023*, n.d.). Albeit these drawbacks, PA amongst other digital advertising tools is still expected to remain its growth at a compound annual growth rate of 21.2% in 2027 (Research and Markets, n.d.).

1.1.2 PA and online retailing

PA is the future of display ads (Aslam & Karjaluoto, 2017; Chen et al., 2019; Choi et al., 2020; Li et al., 2017) as it operates complicated tasks simultaneously and effectively (Chen et al., 2019). By employing PA approach, retailers are enabled to offer products that fit the needs of consumers in a timely manner, and to obtain prompt responses from consumers with low cost and optimal spending budget (Chen et al., 2019; Samuel et al., 2021), which is considered as a need-based targeting method (Ciuchita et al., 2022). Despite the fundamental goal of maximized exposures to the target consumers through relevant ads in timely manner, PA's primary goal is to maximize the return on investment over time (Malthouse et al., 2018) (for advertisers). Studies has shown that ads are shown in website with high-quality context are more beneficial for advertiser (Li et al., 2017; Shehu et al., 2021), which are retailers in this study. However, the retailers lose control over the context to place the ads (Aslam & Karjaluoto, 2017; Ciuchita et al., 2022; Shehu et al., 2021) as the publishers handle the ads serving and delivery (Li et al., 2017). On the other hand, by being exposed to PA-enabled ads, consumers are provided with more relevant ads, speedy interaction with the organizations (Ciuchita et al., 2022), and be able to adjust the behavior accordingly such as going to the closest stores after seeing the ad (Malthouse et al., 2018). Thus, relevancy and timing are the key determinant leading consumer positive attitudinal effect on the ad they see. This effect can increase the likelihood of intention to purchase the advertised products. Meanwhile, high level of customization in the ad is considered as intrusive. (Zhang et al., 2020). This may lead to consumer's negative attitude towards the ads, and increase the possibility of ad avoidance (Yulita et al., 2022)

1.1.3 Theorical development - The TRA and SOR theories

Attitude has been one of the primary research topics in the field of psychology owing to its wide implication at either individual or community level (Fishbein, 1967). Amongst which, the theory of reasoned action (TRA herein) proposed by Fishbein and Ajzen (1975) has been widely applied in various study context such as health, politic, and marketing research (Ajzen & Fishbein, 1980). TRA studies the salient beliefs forming individual attitude towards the behavior of interest in performing or not performing a target action. This means the individual's beliefs influence the relationship between attitude and its affective variables (Zhang et al., 2020). In marketing research, TRA has been widely applied to study the formation of individual attitude in different study contexts such as gaming, banking, social media, and e-commerce, (Anubha & Jain, 2022; Ciuchita et al., 2022; Duffett, 2015; Kaushal & Kumar, 2016). As pointed out by Ajzen and Fishbein (1980), TRA has been famous in studying consumer research due to its strong theorical link between attitude theory and the evaluative criteria. Hence, TRA is applied in this study to seek for the connection between consumer attitudes and its determinants.

Additionally, this study also employs the second theory to construct the environment for the hypothesis model, which is known as stimulus-organism-response (SOR) theory. SOR theory was first proposed by (Mehrabian & Russell, 1974) and has been extended and applied in various studies contexts including shopping behavior (Eroglu et al., 2001; Jayanti & Tasrim, 2023; Peng & Kim, 2014; Zhang et al., 2020), money as a driver of financial inclusion (Shaikh et al., 2023). SOR consists of three elements of stimulus (S), organism (O), and response (R). It aims to explore the role of environmental factors (S) in triggering one's motivation (O) to take behavioral responses (R). The stimulus consists of a list of attributes that influence and provoke the studied organism to act. (Eroglu et al., 2001). Environmental stimulus influence consumers' feelings and emotions leading them to perform particular behaviors (Zhang et al., 2020).

SOR theory is well-known for its focus on establishing relationship between environmental stimulus and the organism, which is aligned with the main purpose of this study. Therefore, SOR framework is employed to focus on studying the effect of PA's characteristics as relevance, timeliness, and intrusiveness on consumer attitudes. In the context of this study, perceived ad relevance, timeliness, and intrusiveness are selected as environmental factors stimulating consumers' attitude towards PA-enabled ads to make determined response as purchase intention and ad avoidance. By applying SOR, the study aims to establish relationships between PA's main characteristics and consumer attitudes.

1.2 Study objective and research questions

Consumer behaviors has been a significantly pivotal research topic in various disciplines, and has been improved and evolved since its first existence (Bray, 2008). However, little is known about how consumers behave in the context of PA. Regarding PA, although its immaturity in the landscape of digital advertising, it has been gaining attention from both academic and practitioners in recent years (Li et al., 2017) owing to its capabilities to optimize the effectiveness of advertising campaign that precisely and effectively targets the right audiences with lower cost (Busch, 2016). Being inspired by these reasons, this study's main objective is to explore the impact of ad enabled by programmatic technologies on consumers' attitudes leading to corresponding behaviors. Two corresponding behaviors in this study includes online purchase intention, and ad avoidance.

Programmatic advertising main features focus on personalization and automation (Busch, 2016; Ciuchita et al., 2022). Consumers are proven to benefit from ad enabled by PA since it provides related information what meet consumer's current concerns and interests. In addition, consumers can make swift interaction with the retailers as they can adjust their behaviors according to the timely displayed ads. This will hardly happen without the assistance of the relevant ads in a timely manner. Research have shown that relevancy and timeliness of the displayed ad significantly positively influence consumer's attitude towards the ad (Feng et al., 2016; Zhang et al., 2020), while perceived intrusiveness exerts negative attitudinal effect in consumers (Samuel et al., 2021). This study aims to explore the impact of ad relevance, timeliness, and intrusiveness on consumer's attitude towards PA empowered ads. Consequently, it leads to the study's first research question. Furthermore, consumer's attitude has a positive relationship with purchase intention in the context of in-game advertising (Anubha & Jain, 2022), and social media (Duffett, 2015; Sebastian et al., 2021). Hence, this study seeks to explore the same connection in PA environments. This is the second research question. Given the effectiveness of PA-enabled ads, consumers have shown to develop negative attitude towards the ads, which triggers them to abandon seeing the ads. Therefore, the study seeks to explore the negative effect of PA=enabled ads exerting to consumers leading them to avoid the ads. The third question represents this.

Research objective:
1) To contribute to the TRA and SOR theories in the context of PA.
2) To understand the impact of perceived ad relevant, timeliness, and intrusiveness enabled by programmatic technologies on consumer's purchase intention and ad avoidance.

Research questions:
RQ1: To what extent, ad relevance, timeliness, and intrusiveness as products of programmatic advertising affect consumer attitude towards PA?
RQ2: To what extent, consumer's attitude towards PA influences their intention to purchase the advertised product or service online?
RQ3: How consumer's attitude towards PA influences their avoidance behaviors?

FIGURE 1 Research objective and questions

1.3 Structure of the study

This master's thesis is divided into five main parts. In the first part, a theoretical framework is introduced. It includes the applied theories of TRA and SOR, which are placed as a backbone for building the research model. In addition, online display ad landscape is mentioned to give a background knowledge about the environment where PA ads operate. After that, programmatic advertising is represented regarding its overview, ecosystem, model, and process. Previous study and literature related to the present study's constructs are included. They are perceived ad relevant (REL), perceived timeliness (TIME), perceived ad intrusiveness (INTR), consumer's attitude (ATT), purchase intention (INT), and ad avoidance (AVDN).

The second part of this study explains the proposed hypotheses and research model. It is proposed that REL, and TIME have positive connection to ATT, while INTR negatively affects ATT. Moreover, ATT has a positive relationship with INT, but has a negative one with AVDN. Research methodology is displayed in the third part. Quantitative research methodology with online questionnaire method was chosen owing to its effectiveness regarding time and budget. In this section, the process of data collection is described in detail together with questionnaire design. Data analysis procedure explains how variables are formed accompanied by statistical software used in analyzation process. As data was collected via online questionnaires, it is important to detect common biases to prevent misleading results. Hence, common method variance (CMV) is used.

The fourth part of this study introduces the study findings and its analysis. Respondents' demographic and background information was analysed by IMB SPSS Statistics for descriptive analysis while SmartPLS 4 was employed to evaluate the inner and outer model of the research. The measurement model assesses the constructs' reliability and validity while the structural model evaluates hypothesized relationships between constructs. In the last section, theorical and managerial implications are discussed together with the study's limitations and potential for future research.

1.4 Key terms

AI	Artificial Intelligence
CMP	Content management platform
CMV	Common method variance
PA	Programmatic Advertising
OBA	Online behavioural advertising
DSP	Demand Side Platform
SSP	Supply Side Platform

DMP	Data management platform
PCP	Programmatic creative platform
DCO	Dynamic content optimization
PAC	Programmatic advertisement creation
RTB	Real-time Bidding

2 THEORETICAL FRAMEWORK

This section aims to first introduce the theories of TRA and SOR providing frameworks for constructing hypotheses model. TRA is used to explain the connections between attitude and its evaluative criteria while SOR provides a stimulating environment for consumers' behavioural responses. The following section represents background information of programmatic advertising, and its characteristics followed by prior literatures about consumer's perceived ad relevance, timeliness, and intrusiveness. In addition, literatures about purchase intention and ad avoidance in PA context are also represented.

2.1 Theory of Reasoned Action

The theory of reasoned action (TRA) was first introduced in 1967 by Fishbein. Since then, it has been adjusted and evolved. The theory's name is formulated according to its assumption of human rationality. This means human beings take advantage of available information in considering a particular action prior to performing it. The theory's primary goal is to foresee and understand a behaviour performed by an individual. Hence, it is important to pinpoint and measure behaviour and its determinants. According to TRA, intention is an immediate determinant of a behaviour of interest. A person's intention is determined by one's personal thinking and the social environment that one is surrounded by. (Ajzen & Fishbein, 1980).

To understand one's intention to perform or not perform a particular action, it is important to study determinants of that intention. According to Ajzen and Fishbein, these determinants are attitude towards the behaviour and subjective norms. Attitude toward the behaviour prefers to a person favourably or unfavourably performs the behaviour in question. This is resulted from one's positive or negative thoughts of performing the behaviour. The second determinant of intention is subjective norm. This occurs when the perceived social pressure influences one's decision to perform or not perform a behaviour of interest. In TRA, social norms are formed by a set of salient beliefs that either motivates or restrict the behaviour performance. The social pressure is generated from one's important people such as family members or close friends. (Ajzen, 2012; Ajzen & Fishbein, 1970; Fishbein & Ajzen, 2009)

TRA has been widely applied in numerous study contexts to predict and understand human behaviour in tourism (Ryu & Han, 2010), health behaviour (Conner et al., 2017), and consumer behaviour ((Belleau et al., 2007; Borusiak et al., 2020; Copeland & Zhao, 2020). Albeit its popularity, TRA has restriction when being applied in the field of consumer research. However, researchers in the field of marketing remain interested in TRA to study attitude due to its theorical link between evaluative criterion and attitude (Fishbein & Ajzen, 2009; Zhang et al., 2020). To be able to understand and predict a behaviour, it is required the measured behaviour of interest to include its directed target of behaviour, specific context, and time in which the behaviour is performed. However, in the context of consumer behaviour research, most of the studied target is a product or a brand, not a particular action. (Ajzen & Fishbein, 1980, p.34).

This study applies TRA owing to its theorical link between attitudes and its evaluative criteria including ad relevance, timeliness, and intrusiveness. While the study aims to understand consumer's targeted behaviour as purchase intention and ad avoidance, its primary focus is laid in the context of consumer's attitude toward displayed ads enabled by the PA technology. Although its targeted behaviour, which is to purchase and to avoid, and behavioural context of online shopping meet the criterion of TRA, it does not include set of specific time. Besides, the scope of this study is not fully exploring the TRA model but concentrates on consumer intention to purchase instead of the purchase behaviour itself. Therefore, this study selectively adopts the TRA's framework of attitude formation targeting the determinant of attitude towards PA ads.

2.2 Theory of stimulus-organism-response (S-O-R)

Besides TRA, this study also applies stimulus-organism-response (SOR) theory to construct our research model. SOR was first proposed by (Mehrabian & Russell, 1974), which demonstrated the encouraging role of the surrounding environment (stimulus) on individual's internal state (organism) to lead to a particular behaviour (response). SOR model has been broadly applied in studying various behavioural studies including consumer behaviour. (Anubha & Jain, 2022; Zhang et al., 2020). The first element of SOR model is stimulus, which is environmental factor influencing consumer's perception and triggers their responses. Organism is the second SOR's element, which acts as an intervening factor between the stimuli and final response. Consumers retrieve information from their evaluation of the provided stimuli to understand the environment prior to make any judgement or decision. This leads to the third SOR's element, which is response. (Anubha & Jain, 2022). Generally, SOR theory emphasizes the mediating role of individual's emotional state in the relationship of environmental stimuli and their behavioural response (Zhang et al., 2020).

In the context of this study, relevance, timing, and perceived intrusiveness are the selected stimuli. PA provides advertisements that match consumer's current preferences in real time with the support of AI application. Hence, personalization and automation are the main characteristics of PA (Ciuchita et al., 2022). Previous studies have proposed ad relevancy, and timeliness have significant influence on consumer's attitude towards the ad (Ciuchita et al., 2022; Feng et al., 2016; Zhang et al., 2020). However, ads served with high level of personalization is considered as intrusive (Zhang et al., 2020). These three stimuli create an environment that affect consumer's attitude towards PA enabled ads. On the other hand, consumer's attitude towards the PA enabled ad is the chosen organism, which mediates the impact of ad relevance, perceived timeliness, and intrusiveness on their behavioural responses toward the environmental stimuli. The selected behavioural responses are their intention to purchase the advertised product or service online, and avoid ad.

2.3 Online display advertising landscape

This section aims to provide a general introduction about the landscape of online display advertising in which programmatic advertising operates and facilitates. Besides, the relationship between online display advertisements and programmatic advertising is mentioned.

2.3.1 Online display advertising overview

Owing to the booming Internet usage, Internet advertising plays a crucial role in companies' success. Thanks to its benefits as awareness and recognition building, improving positive brand attitude, and generating direct responses, online display ads has been gaining its importance in today marketing practice (Paulson et al., 2018). According to the Interactive Advertising Bureau (IAB herein) report, digital advertising revenue in 2022 was more than 200 billion US dollars for the first time. In the US market alone, internet advertising revenue has been increasing despite the economic downturns and new regulations concerning data privacy. Programmatic advertising revenue was observed to have continuous growth with the year-on-year growth by 10.5% compared to the previous year showing its strong resilience against the plummeted economy. Amongst the five compared advertising formats, display ad revenue valued 56.7 billion US dollars, which increases 29 percent compared to 2020 and accounts for 30 percent of the total internet ad revenue. (IAB 2023).

2.3.2 Online display ads and programmatic advertising

Display ads are shown based on a consumer's past behaviour in entering keywords query in the search engine. Later on, when the consumer browse other websites, the ads that related to the previously search will be presented in various content, duration, event, and formats. (Aslam & Karjaluoto, 2017; Zhang et al., 2020). The nature of display advertising lays in buying and selling digital ad spaces between advertisers and publishers. The display ad ecosystem has been evolving with the increasing participation of different players leading to higher complexity within the system (Aslam & Karjaluoto, 2017). Subsequently, companies face more challenges in deciding where to place online display ads to optimally allocate spending budget.

Marketers has been facing various challenges in today fluctuating environment, particularly consumer's online usage. Thanks to the advance development of Internet and smartphone, consumers have been able to access online materials faster than ever before. Hence, marketers can have greater opportunities to provide advertisements to online users. However, due to consumers' shortened time and attention span leads to higher demand in more relevant contents. Meanwhile, despite the tremendous growth of the Internet, online marketing's transition to automation is slow compared to conventional ones. Altogether, there exists an urgent need for change in advertising ecosystem, which can be tackled with programmatic advertising. (Busch, 2016, p.3). The practice of employing automation in assisting the ad-buying and selling process is known as programmatic advertising (Paulson et al., 2018).

2.4 Programmatic advertising

This section represents main characteristics, and functions of programmatic advertising in relation to online retailing context. Firstly, a brief overview about programmatic advertising market is introduced followed by its ecosystem and model. In the ecosystem, the role of three players is highlighted together with their responsibilities and capabilities towards programmatic advertising operation. Thirdly, the programmatic advertising model represents a holistic view of different platforms that jointly elaborate each other to create successful ad strategies.

2.4.1 Overview of programmatic advertising

The definition of Programmatic advertising (PA herein) in the current digital landscape is ambiguous (Busch, 2016; Chen et al., 2019; Malthouse et al., 2018; Samuel et al., 2021). The term PA is used interchangeably with programmatic media buying (Chen et al., 2019), or real-time advertising (Busch, 2016). As defined by Digital Marketing Institute (*Programmatic Advertising | Glossary*, n.d.), PA is "a type of advertising that uses artificial intelligence to build audience profiles". Busch (2016) prefers PA as a combination of data, technology, and artificial intelligence (AI herein) to enhance marketing effectiveness in real-time. Meanwhile, Li et al., (2017) considers it as a big data-driven tool for precision marketing since its ability to precisely target potential audiences and real-time allocating ad resources. Others like Malthouse et al., (2018) states that PA applies the computational advertising approach in which ad buyers (as retailers) can purchase exposures through automated auction in real-time ad exchange market.

Amongst the recent definition of PA, Samuel et al., (2021, p.2) generated, so far, the most holistic view of PA's definition which defines it as:

"An automated big data system organization (predominantly retailers) to bid for the privilege to publish personalized online advertising in the right place, to the right people, at the right time".

Hence, PA is distinguished from traditional advertising thanks to high level of personalization, behavioural retargeting (Ciuchita et al., 2022; Zhang et al., 2020), and timely provided ads (Busch, 2016, p. 8; Zhang et al., 2020). On the other hand, these distinguishing elements also brings mixed consumers' responses toward the ad as customers perceive the ad is intrusive. (Ciuchita et al., 2022; Samuel et al., 2021; Zhang et al., 2020). Consequently, it leads to ad avoidance (Bang et al., 2018; Cho & Cheon, 2004; Jung, 2017).

PA has been gaining its popularity as a result of the increasing complexity and fast evolving in online display ads landscape together with the rapid change in consumer's online usage (Li et al., 2017). It is believed to have been disrupting the advertising ecosystem in maximizing the advertising budget while reducing waste circulation for ads (Busch, 2016, p. 26; Samuel et al., 2021). PA is considered as the future of display advertising (Aslam & Karjaluoto, 2017) as it resolves the traditional marketing's problem of merging purchasing and selling process of ads space effectively (Busch, 2016). Despite PA's great opportunities, it is considered as a threat to advertisers, agencies, medias, and sales houses due to the complexity of involved technology (Busch, 2016, p. 7). On the other hand, PA is believed to add significant values to publishers' media plan as an effective sales channel but branding goals nor performance measurement (Busch, 2016, p. 12).

2.4.2 Relationship between PA and Metaverse

Metaverse is a virtual world mimicking the physical one where the immersive combination of enterprises, data, and communication tools occurs. This highlights its potential beyond a gaming platform to become a new marketing universe (Hollensen et al., 2022; McKinsey, 2022). Among the key features of metaverse is programmatic advertising (McStay, 2023). The relationship between metaverse and programmatic advertising has been studied (Amironesei, 2023), highlighting its potential benefits and challenges.

Programmatic advertising is considered as one of the core business features in metaverse where precise target marketing can be applied so that brands can target specific groups of consumers based on their interests. Meta, as one of the leading companies in metaverse, has been utilizing programmatic technology to create automated in-game advertising based on consumer preferences. This results in the existence of hyper-personalization wherein ads can be automatically customized to suit customer preferences. (McStay, 2023). Hence, it is crucial for companies to have a well-established strategy for programmatic advertising on metaverse, which is continuously updated with latest trends and technology developments. Despite of its novelty, metaverse still provides a promising virtual platform for brands to engage with their customers, especially gen G, who are keen on experiencing new technologies and are quick to change and adapt.

2.4.3 PA ecosystem

PA rooted from display advertising (Aslam & Karjaluoto, 2017) and has been developed and become one of the most evolving advertising information technology phenomenon (Li et al., 2017; Samuel et al., 2021; Zhang et al., 2020). The ecosystem of PA inherits the characteristics of display ads ecosystem. According to Choi et al., (2020), the display ad ecosystem consists of key players, selling channels, and display ad market's key traits. Their studies states that advertisers, publishers, and intermediaries are three main key players involving in the media buying and selling. Advertisers purchase ad exposures on publishers' website, and publishers provide ad inventory for advertisers in return for high monetary gain. In the PA current market, publishers can sell ad impressions either publicly via real-time bidding (RTB herein) or privately via private marketplace (PMP herein), guaranteed buying or preferers.

Beginning in 2007, RTB has been gaining its popularity (Zhang et al., 2020). RTB has been widely applied and dominated the PA atmosphere as it is empowered by advanced technology offering dynamic pricing scheme in a timely manner (Yuan et al., 2014); therefore, it is unavoidable to be confused PA as RTB, and vice versa. In RTB, publishers ask publicly for all advertisers to place bids. Depending on the bids, ad impressions will be sold differently in quantitative. In contrast, via private marketplace, publishers send private invitation to selected advertisers to participate in auctioning for high-quality ad exposures. (Choi et al., 2020). Since publishers have control in ad impression delivery channels, the disclosure of information in ad auctions is unclear; therefore, different information structure is reported for advertisers. (Li et al., 2017). The third player is the intermediaries that enable advertisers and publishers to match through data managing and serve ads with the help of automation and algorithms (Choi et al., 2020). These intermediaries consist of demand-side platform (DSP herein), supply-side platform (SSP herein), ad exchanges, ad networks, and data aggregator (Aslam & Karjaluoto, 2017; Chaffey, 2021; Choi et al., 2020).

Regarding the selling channels, the guaranteed and nonguaranteed channels facilitate ad exposure to be sold either directly at fixed-price or through ad exchanges in real-time. Pricing mechanism, ability to target, and the engagement level of intermediaries are the main distinctions between guaranteed and nonguaranteed selling channels. In guaranteed selling channels, advertisers purchase a bundle of ad exposures from publishers at a negotiated price. During this negotiation process, publishers employ programmatic buying technology known as programmatic direct to automate the contracting process. This allows smaller advertisers to negotiate albeit limited budget. (Choi et al., 2020).

On the other hand, in the nonguaranteed selling channel known as real-time bidding, advertisers are asked to place bid for a single exposure in real time with the help of programmatic buying. By conducting media selling through RTB, publishers can gain high ad selling, while advertisers can better target potential consumers based on their specific information. Due to the complexity of RTB, DSPs facilitate managing bidding process for advertisers while SSPs smoothens the inventory management and its optimization for publishers (Choi et al., 2020). In the context of online retailing, publishers and advertisers, however, may not yet fully understand consumer's perception about the employment of RTB advertisements (Zhang et al., 2020).

Figure 2 displays the ecosystem of programmatic advertising, which is divided into buyer side and seller side. After a customer opens a webpage provided a publisher, the ad server on the publisher site will inform via SSP that the ad inventory is ready to be purchased. The DSP accesses the information and inform advertisers about the available ad inventory. Via agency trading desk or in-house team, a content that suitable for the customer will be prepared and placed a bid (Chaffey, 2021).

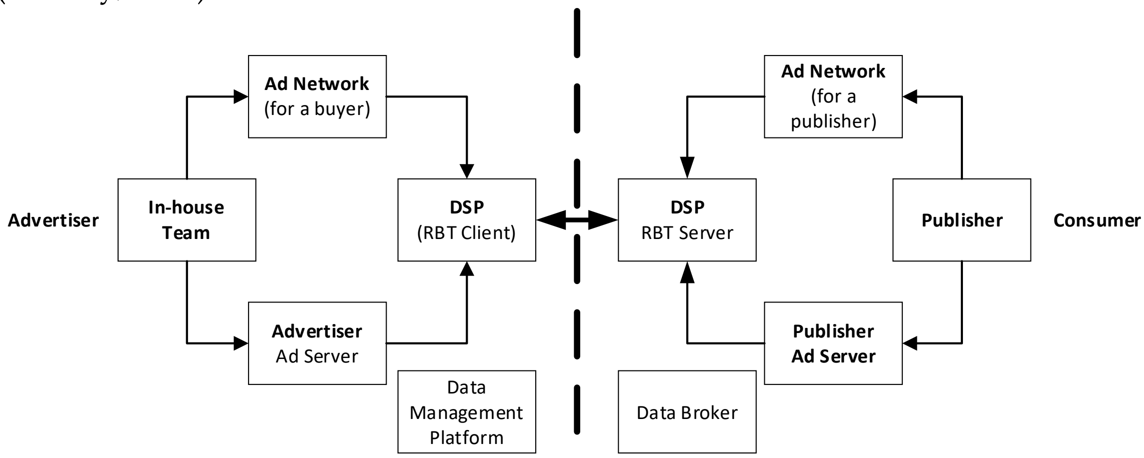

FIGURE 2 PA's ecosystem (Chaffey, 2021)

2.4.4 PA model

PA is considered as an ad-impression-buying model (Li et al., 2017) enabled by the advance technology of artificial intelligence to act as a platform for buying and selling ad exposure (Chen et al., 2019). Regardless of this, Chen et al., (2019) points out that PA has been narrowly defined as programmatic media buying. In their study, they propose the model for PA including programmatic buying and programmatic creative, in which the latter one refers to the media creation, as shown in figure 3. Although the AI technology behind programmatic buying has been well developed, AI-enabled programmatic creative has made humble process owing to the underdeveloped machine learning algorithm and big data within this subject. (Chen et al., 2019). Subsequently, Chen's study has been so far the first to explore the AI-enabled creative process of PA.

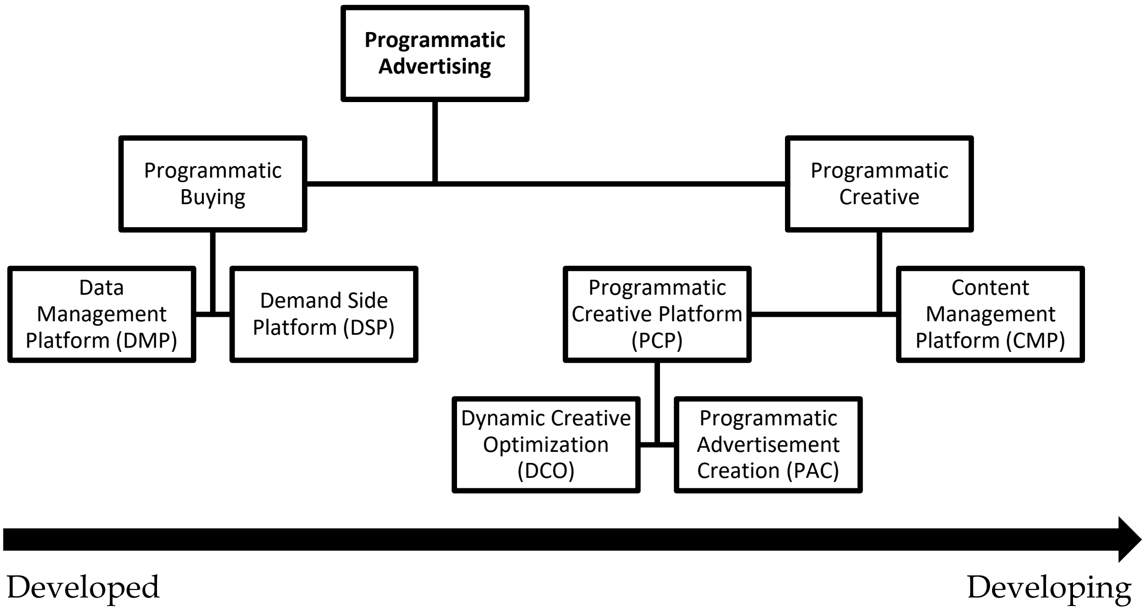

FIGURE 3 The model of programmatic advertising (Chen et al., 2019)

As being displayed in figure 3, the programmatic buying includes data management platform (DMP) and demand-side-platform (DSP), which aims to find the suitable ad space for placing individual advertisements. Both platforms are underpinned by machine learning algorithms. DMPs with the employment of AI, can collect a huge amount of Internet user data, known as big data, in variety, volume, and velocity. Machine learning algorithm collects multidimensional user data and creates single tags for each piece of collected data, which can be easily retrieved. This helps advertisers form a holistic view about an Internet user. Besides, with the collected data, DMP can generate segmentation profile by selecting and mixing the tags. As new data is continuously generated, DMP can offer real-time content that matches user's current behaviour. In return, advertisers can receive user feedback in real-time so that they can swiftly adjust the ad performance. (Chen et al., 2019).

DSPs, on the other hand, is the main function of AI-facilitated programmatic buying as it employs machine learning algorithm in performing complicated and speed-demanding bid placement. Consequently, advertisers can purchase digital ad space in milliseconds with an effectively consumer targeting approach. The bidding is made based on the predicted click-through-rate (CTR herein) generated by DSP. (Chen et al., 2019). In RTB, owing to real-time decision making, predefined bidding guidelines are applied to support DSP algorithms to decide the bid for available exposure. Most DSP algorithms are rule-based, proprietary and designated for single ad impression (Paulson et al., 2018). Therefore, the study conducted by Paulson et al., (2018) proposes a non-proprietary algorithm formulation for optimally allocating budget, which considers the viewership correlations across multiple websites instead of merely following a set of guidelines.

The programmatic creative assists advertisers in automating the process of creating personalized and contextualized ads. It consists of programmatic creative platform (PCP) and content management platform (CMP). PCP includes dynamic creative optimization (DCO), and programmatic advertisement creation (PAC). DCO collects real-time consumer feedback on displayed ads so that PAC can utilize these insights to enhance the performance of ad content creation. Advertisers can flexibly decide high or low automation level PCP so that ads can be created at large-scale with high personalization level and better targeting capability. Since a consumer is constantly changing in terms of attention, attitude, and needs, it is crucial that PCP collaborates with DSP and DMP to create and show the ads accordingly. (Chen et al., 2019).

2.4.5 PA's process

According to Busch (2016), PA's main principles focus on granularity in budget optimization and automation in the ad trading process. After an online user visits a website, the PA process starts. Advertiser send a request sent to DSP for an ad campaign provided with target budget, audience, and duration. The website communicates with SSP on behalf of the advertisers to ask for an ad placement. SSP such as CNN.com collects Internet user's data from its website through the web browser. The collected data includes details of the user's preferences, contact information, and location. Before publishers send the ad request to SSPs, they first check the availability of the contracted advertisers. SSPs, after receiving the ad request from publishers, send a bid request to all DSPs. The bid price determined based on the advertisers' request is sent to a particular SSP. After notifying the winning bid, SSP asks for an ad and send it to the publisher to display. (Aslam & Karjaluoto, 2017). This whole process takes milliseconds to complete (Busch, 2016; Chen et al., 2019; Choi et al., 2020; Li et al., 2017; Samuel et al., 2021; Zhang et al., 2020).

2.5 Perceived ad relevance

2.5.1 PA as Online behavioural advertising approach

PA is a form of online behavioural advertising (OBA herein) as it creates ad message based on the collected data of consumer's online behaviour such as their interaction with the company, or searching habits (Li et al., 2017). OBA is a form of data-driven digital advertising, which is characterized by its monitoring and tracking consumer behaviour online, and its use of collected data for creating targeting ads (Boerman et al., 2017; Varnali, 2021). By employing this approach, advertisers can provide personalised advertisements that matches consumers' interest. As a result, personalization advertising allows advertisers to build a relationship with targeted consumers by heightening their experience with retailers.

Consumers are more likely to show positive acceptance towards the personalized ads if they are relevant, useful, and credible (Zhang et al., 2020). Hence, advertisers are suggested to pay more attention to ad relevance as it effectively enhance consumers acceptance towards the ad (Aiolfi et al., 2021).

2.5.2 Role of AI in personalization

Artificial intelligence (AI) is defined as "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p.5). AI-enabled personalization (AIP) supports consumer buying journey by gathering, classifying, analysing, and applying consumer data from their interaction with the company before, during, and after purchase procedure (Gao & Liu, 2022). In the context of PA, tasks such as personalized recommendations and designing ads messages are performed by a combination of narrow AI modules (Chen et al., 2019). Artificial narrow intelligence means that AI can merely perform the determined tasks without ability to autonomously solve issues that they are not designed to (Kaplan & Haenlein, 2019). Therefore, it is crucial to have human intervention in the AI-enabled programmatic process (Samuel et al., 2021).

Since its existence, research of AI's application can be detected in various fields including service (Flavián et al., 2022; Huang & Rust, 2018; Meyer et al., 2020), advertising creativity (Vakratsas & Wang, 2021), consumer relationship (Bag et al., 2021; Cheng & Jiang, 2021; Kishen et al., 2021; Kumar et al., 2019; Puntoni et al., 2021; Rana et al., 2021), programmatic advertising (Chen et al., 2019; Diwanji et al., 2022). It can be observed that despite the immature of AI's related research in the PA, it has been rapidly growing and developing. Despite its tremendous application in PA practice, there exists a humble amount of academic research regarding this topic. It is possible to say that AI has been profoundly emerged in PA, particularly in programmatic creative side. However, it has raised consumer's concerns as they perceive AI as a cognition-driven tool. Hence, it is less capable of performing emotional-related tasks. The study conducted by Bakpayev et al., (2022) shows that consumers prefer ad created by human agents or human-like AI for emotional and hedonic products. Regarding utilitarian products, the study suggests AI-enabled programmatic creative should be gradually employed with rational appeals to improve consumer's acceptance. Being able to provide customized ads at the right time is the main characteristics of PA, hence advertisers are advised to apply AI in creating personalized ads so that consumers will likely accept.

2.5.3 Personalization in ad relevancy

Personalization approach has been employed in various field and contexts ranging from business, education, entertainment, and marketing. In the context of marketing, personalization is a wide concept including the implementation of personalized marketing and its output, value creation for the both consumer and advertisers (Vesanen, 2007) to enhance marketing performance. Companies takes advantages of consumer data collected either internally or externally to build a consumer profile prior to design customized messages and deliver it to the consumers (Vesanen, 2007; Vesanen & Raulas, 2006). This process can be enabled by AI (Gao & Liu, 2022). In the context of location-based advertising, ads provided by location-congruence are perceived as relevant and valuable (Hühn et al., 2017). Regarding the ecommerce context, personalization can influence consumer's attitude toward the display advertisements either positively or negatively (Zhang et al., 2020). Although personalized marketing approach has been highly praised by academics and companies for its various benefits, it has generated opposite opinions from practitioners concerning ethical issues (Strycharz et al., 2019).

2.6 Perceived ad timeliness

Ads shown in a timely in according to customer's need is known as need-based targeting (Ciuchita et al., 2022). Being able to provide the ad in a timely manner allows advertisers to activate consumer positive impression toward the advertised company (Merisavo et al., 2007); consequently it contributes to the success of advertising (Ho et al., 2011). Although the definition of timeliness slightly differs in different context, it firmly focuses on consumer's perceived utilitarian values derived from the ad (Feng et al., 2016; Hourahine & Howard, 2004; Zhang et al., 2020). This means the information provided by the displayed ad will be most useful for consumers when they are most needed. For example, instead of manually inserting keywords for every single product, consumers are recommended with similar range of products relating to their current interest. Hence, consumers can significantly save time in searching and comparing similar products either from the same or different brands before making purchase decision.

Timeliness is especially crucial for advertising low-engagement products (Bellman et al., 2013) and services in critical timing (Hourahine & Howard, 2004). Research has shown that ad shown with time conscious has a proven positive influence on attitude towards the ad (Zhang et al., 2020). Consumer's perceived timeliness toward the ad has been studied in the context of mobile advertising (Feng et al., 2016; Merisavo et al., 2007), web personalization (Ho et al., 2011; Tam & Ho, 2005), TV commercials (Bellman et al., 2013), and RTB (Zhang et al., 2020).

2.7 Perceived intrusiveness

Intrusiveness is defined as a measuring factor on how much an ad causes undesirable distraction while an internet user is performing a task. Although online ads are designed to interrupt Web users to attract their attention, the content obstruction caused by online ads is recognized as intrusive. There are various studies about intrusiveness in both traditional and online advertising environments. Despite the positive results, studies showed that consumers perceive online ads as disturbing and annoying. Compared to other media consumers, online ones tend to find online ads more intrusive; consequently, they develop an irritating feeling towards the ads and will probably not return to the website (McCoy et al., 2008). Irritation is a negative attitude associated with unwanted ads that either shows in an offensive manner or overly manipulate consumer's online activity (H. C.-S. Lin et al., 2021). In addition, high product involvement leads to high level of privacy concerns and intrusiveness (Lim et al., 2023).

Online ads are considered as intrusive as displayed on private, social and entertainment websites (McCoy et al., 2008). Intrusiveness have shown to be one of the elements directly influence consumer's negative attitude toward PA due to the high level of personalization in the ads (Aiolfi et al., 2021; Samuel et al., 2021; Zhang et al., 2020). If consumer's privacy concern is understood as the wrong usage of personal data (Palos-Sanchez et al., 2019), consumer's perceived intrusiveness occur when the ads are served with high level of accuracy according the consumers' preferences and online behaviour. Hence, intrusive ads can creep consumers out (Yun et al., 2020).

2.8 Attitude towards PA and online shopping intention

Consumers who have positive attitude towards the shown ads are more likely to intent to click for more information (Aiolfi et al., 2021). Click intention indirectly prefer to the high level of interest in the product and high intension to product purchase. Consumer's attitude towards advertising has drawn researchers' attention; and proven to have a direct relationship towards the advertised brand. This enhances the likelihood of consumer's buying intention (Duffett, 2015). Positive attitude towards the shown ad also increases the possibility of clicking the ad. Click intention shows consumers' willingness to opt for further details about a product or a service. Therefore, it is considered as the behavioural predictor that consumers perform on the first stage of the buying process as it. (Aiolfi et al., 2021). Consequently, the likelihood of purchase intention an advertised product increases when the level of click intention increases.

Consumer purchase intention has been a widely studied topic in numerous context including tourism (Talwar et al., 2020), blockchain (Dionysis et al., 2022), social media (C. A. Lin & Kim, 2016; Nasir et al., 2021), mobile advertising (Feng et al., 2016; Merisavo et al., 2007), chat-bot (Pereira et al., 2021), online shopping (Achar et al., 2016; Hansen et al., 2004; Karampournioti & Wiedmann, 2022; Yen & Chiang, 2021), computational advertising (Huang & Liu, 2022; Sivathanu et al., 2022), to name a few. Albeit this lengthened list of applied contexts, it is hard to detect any research on consumer's intention to purchase in the context of programmatic advertising.

Purchase intention refers to a consumer's plan to buy a product or service in the future (Kaushal & Kumar, 2016). Previous studies have shown that when consumers have positive attitude toward the display ads, they probably have positive attitude towards the retailer (Anubha & Jain, 2022; Ciuchita et al., 2022; Duffett, 2015; Sebastian et al., 2021). As a result, consumers are more likely to intend to purchase the advertised product or service (Anubha & Jain, 2022; Duffett, 2015). In the context of in-game advertisement, Anubha and Jain (2022) study gamers attitude toward the advertised brand as a mediator in strengthening the relationship between gamers' stimuli to play and intention to purchase. A study conducted by Duffett (2015) about millennials behavioural attitudes towards Facebook advertisement also shows the positive relationship between users' attitude towards the Facebook ad and their intention to purchase.

2.9 Ad avoidance

Avoidance of ads is associated with a consumer's belief towards the adverts, and is considered as a media user's style (Mikael, 2012). Ad avoidance is defined as users' action in reducing their exposure to the advertising materials (Speck & Elliott, 1997). It also refers to consumers' resistance cognitively, affectively, and behaviourally in avoiding the ads (Cho & Cheon, 2004; Dodoo & Wen, 2019). A consumer can cognitively ignore the ads, behaviourally click pass the ads (Speck & Elliott, 1997) or possess a negative affection towards the ads (H. C.-S. Lin et al., 2021).

Consumers tend to avoid the ads when they are sceptical about the shown ads, and perceive the ads as irrelevant, or intrusive. However, irritating feeling towards the ads is believed to be the most important key drivers of ad avoidance. (H. C.-S. Lin et al., 2021). Research has shown that consumers' irritation and attitude towards the ads directly affect their ad avoidance (Yulita et al., 2022). However, it is noticeable that attitude is the core element determining consumers' ad avoidance behaviour (Vakratsas & Ambler, 1999). It is argued that ad avoidance is a result of general negative attitudes that consumers hold towards advertising (Cho & Cheon, 2004; Li et al., 2002; Mikael, 2012; Yulita et al., 2022). Customers avoid ads when they perceive the shown ads obstruct their online goal, exceeding amount of ads, and their prior negative experience with advertisement (Cho & Cheon, 2004). Based on the work of Cho and Choen (2004), Seyedghorban et al., (2016) extended the research model and found out the role of user mode in mediating the relationship of consumers and their behaviour of avoiding ads. This means, users have more control in deciding whether to see the ads such as installing ads blockers.

In the context of SNS, ad avoidance has been shown to relate to individual's personality traits (Dodoo & Wen, 2019). A research about Finnish media users' behaviours points out that consumers shows different avoidance behaviour toward different media types based on its entertainment, informativeness, and credibility values (Mikael, 2012). In addition, incentive and personalization positively reduce ad avoidance (Yulita et al., 2022). Consumers have the tendency to avoid the ads when they perceive the irrelevant ad interrupting their online activities, especially in the information-seeking process (Bang et al., 2018). Attitude towards the ad also influences consumer's decision in using ad blocker, which is considered as an avoidance behaviour towards the ad (Redondo & Aznar, 2018).

3 RESEARCH MODEL AND HYPOTHESES

This session represents the hypotheses studying the relationship between perceived ad relevance, timeliness, intrusiveness, and attitude towards PA ads. In addition, the relationships between attitude towards PA ads and consumers online shopping intention and ad avoidance are also examined.

3.1 Perceived ad relevance

Personalization has been an attractive subject in current marketing practices and research. Employing personalization approach in placing ads can bring enormous positive changes for the retailers regarding increase in customer attention, and satisfaction (Tam & Ho, 2005). Vesanen and Raulas (2006) considers personalized marketing as a new communication standard with the employment of algorithm and big data. This allows advertisers to utilize personal data, place bid, and maximization of advertisement supply. Research has shown that personalized message is more likely to be processed by consumers when it matches consumer's preferences and consequently makes it more persuasive to the target consumers (Tam & Ho, 2005).

By employing personalization approach, advertisers can generate better click-through-rate (CTR), more banner attention (Strycharz et al., 2019) and better TV commercial targeting (Bellman et al., 2013). Meanwhile consumers feel more convenient, gain economic advantages from free vouchers, coupons, receive more personal-related advertisements (Strycharz et al., 2019). PA consist of personalization of the display ad and automation in placing the ad. Personalisation is one of the raising topics in online ad research (Ciuchita et al., 2022), and is considered as one of the three PA's tension as an integration of personal data analysis and big-data driven technologies (Samuel et al., 2021). In the context of PA, personalization happens when the ad exposures are personalized to reach only interested consumers at predetermined time so that advertisers can achieve the best outcomes (Malthouse et al., 2018). Therefore, personalization brings relevant ad to consumers.

Previous studies have been shown that relevancy increase consumer attention to the ad (Feng et al., 2016; Jung, 2017), increase engagement (Bang et al., 2018), and consumer attitude towards the ad (Ciuchita et al., 2022; Yulita et al., 2022). Consumers perceive an ad as relevant when it relates to their personal needs and values (Feng et al., 2016; Jung, 2017) and preferences (Tam & Ho, 2005). Thus, it increases the advertising effectiveness cognitively, affectively, and behaviourally (Jung, 2017). In order to acknowledge consumers' personal needs, values, and preferences, it is required to collect a huge amount of consumer data generating through interaction with the companies or from third parties (Li et al., 2017). Based on this, advertisers can produce and deliver customized ad message to enhance the ad relevancy to the target consumers (Zhang et al., 2020). Consequently, consumer's perceived ad relevance has positive influence on their attitude towards the ad (Ciuchita et al., 2022; Zhang et al., 2020). Hence, this study aims to explore the relationship between ad relevance as a product of programmatic advertising approach and consumer attitude towards the ad in online retailing. The first hypothesis is proposed as following:

H1. Ad relevance has a positive impact on consumers' attitudes towards PA-enabled ads.

3.2 Perceived ad timeliness

PA ad employs automation to offer the ad to the right consumers at the right time (Samuel et al., 2021), which is known as need-based targeting (Ciuchita et al., 2022). Customers see ads meeting their utilitarian need are more likely to have positive impression towards the retailers (Feng et al., 2016; Hourahine & Howard, 2004; Zhang et al., 2020). In the context of mobile marketing, timeliness has proven to be significant factor influencing consumer's acceptance towards mobile advertising as it impacts their extrinsic motivation (Feng et al., 2016). As a result, it highlights the importance of serving the advertisement at the right time to the right audience.

In the context of PA, ads shown in a timely manner supports consumers in making appropriate and timely decision (Malthouse et al., 2018) as it provides beneficial information to satisfy consumer current preferences (Zhang et al., 2020). With the employment of artificial intelligence in PA, gigantic amount of online consumer data is gathered automatedly and speedily. Based on this, DMPs can create ads message strongly related to target consumer's preferences and promptly provide it to them (Chen et al., 2022; Choi et al., 2020; Gao & Liu, 2022; Li et al., 2017; Samuel et al., 2021). As a result, consumer attitudinal effect towards the displayed ad is likely positive if it is delivered at the right time. In addition to personalized ad, timing is the primary issue impacting consumer's perceived ad relevancy (Zhang et al., 2020). Therefore, the study aims to explore the effect of timeliness toward consumer's attitude towards PA ads. The next hypothesis is proposed as following.

H2. Timeliness has positive influence on consumers' attitude towards PA-enabled ads.

3.3 Perceived intrusiveness

Scaring out customers is one of the challenges PA is facing as computational advertising (Yun et al., 2020). Despite the enormous benefit of AI-enabled advertising approach, customers are highly concerned about privacy intrusiveness. Consumers negatively respond to PA (Paulson et al., 2018) as ads shown with high level of accuracy based on consumer's private preferences and their online behavior increase customer's intrusiveness perception about the ads.

Zhang et al., (2020) studies consumer's concern of intrusiveness in the context of RTB advertisement. The study points out that intrusive feeling is raised when the ads distract and interfere with consumer's online goal-oriented behaviors. This strengthens prior studies regarding consumers' online goal impediments and perceived intrusiveness (Cho & Cheon, 2004; McCoy et al., 2008). Regarding online behavioral retargeting advertising, ads are designed based on collected data about target consumers such as browsing history, location, and preferences. Hence, a tailored ad can be displayed to match online users' current interest. Due to this high level of personalization, PA enabled ads have been proven to negatively impact consumer's attitude towards the ads (Paulson et al., 2018).

In the context of PA, ads are automatedly created based on the real-time data collecting by AI technology and big data. Eventually, it provides highly customized ads to the target audience in a timely manner. This forms consumer's perceived intrusiveness towards the ads. Consequently, the following hypothesis is proposed:

H3. Ad intrusiveness has a negative relationship with consumers' attitude towards PA-enabled ads.

3.4 Attitude towards PA and online shopping intention

Previous studies have shown the positive relationship between consumer's positive attitude towards shown ads and retailers. This leads to consumers' intention to purchase the advertised products or services (Kaushal & Kumar, 2016). This relationship has been significantly confirmed in various marketing platforms and contexts including Facebook (Duffett, 2015), YouTube (Sebastian et al., 2021), in-game advertisement (Anubha & Jain, 2022), to name a few. Consumers have higher tendency to purchase online products after they have a positive impression about the products displayed during their online session. The intentional behaviours can be observed as their willingness to click to the displayed ads to find further details about the products (Aiolfi et al., 2021).

Although consumer attitude and purchase intention are hardly a new concept in marketing research, there are dearth studies about their relation in the context of PA. In retailing context, several studies were conducted to explore the relationship between PA-enabled ads and consumer's attitude (Ciuchita et al., 2022; Zhang et al., 2020). The result shows the positive connection between these two. This means consumers having a positive perception towards the PA-enabled ads are more willing to purchase the advertised products or services. Eventually, this study aims to contribute to the exploration of consumer attitudinal effect on online shopping intention in the context of PA. The next hypothesis is proposed as following:

H4. Consumers' attitude towards PA-enabled ads has a positive relationship with consumer online purchase intention.

3.5 Ad avoidance

Ad avoidance is one of the main challenges for today advertisers (Seyedghorban et al., 2016). It is defined as users' action in reducing their ad exposure cognitively, behaviourally, and mechanically (Speck & Elliott, 1997). Consumer's attitudinal avoidance toward ads can be represented in cognitive, behavioural, and affective ways (Vakratsas & Ambler, 1999). It can be a result of consumers' perception that ads interrupt their online activity, such as bringing significant amount of unnecessary noises, evading their initial searches, and interfering their current Web view (Cho & Cheon, 2004). This is especially important in the information-seeking process (Bang et al., 2018) when consumers actively look for desired information. Thus, consumers will either ignore the ads (Speck & Elliott, 1997) or employ tools to prevent ads to show up such as ads blocker (Redondo & Aznar, 2018).

In the context of PA, ads are generated based on consumer's need demonstrated through their searching behavior. Therefore, highly related ads are served to the target consumers; and the possibility of serving unrelated ads is attenuated. However, ads are shown with high levels of frequency and personalization can irritate consumers. Consequently, they perceive the ads as intrusive, and dislike them. This leads to avoiding seeing the ads. In addition, when consumers ponder that their privacy has been violated due to high levels of personalization involved in displayed ads, they also show a tendency to avoid seeing the ads (Jung, 2017). In contrast, tailored ads matching personal traits have a positive influence on consumer's attitude towards the ads. As a result, it reduces ad avoidance (Dodoo & Wen, 2019). In other words, positive attitude towards the PA enabled ad reduces the likelihood of ad avoidance. Hence, the hypothesis is proposed as follow:

H5. Consumers' attitude towards PA-enabled ads has a negative relationship with ad avoidance.

3.6 Summary of research model

A research model is also known as conceptual model showing the relationship between constructs and variables. It is pivotal to have the conceptual model ready in the early phase of the research process. Constructs and indicators are two main elements of conceptual model. Constructs are measured by the component variables while indicator variables refer to raw data or observation. Unidirectional relationship between constructs or constructs and variables is demonstrated by single-headed arrows. It is highlighted that constructs are placed in a sequential manner in accordance with prior theories (Hair et al., 2015, p. 154).

Figure 4 represents this study research model consisting of six constructs placed sequentially corresponding with theories of TRA and SOR. All the constructs are connected to each other by single-headed arrows, which the one on the right is the sequential outcome of the left constructs. In addition, perceived ad relevance (REL), perceived timeliness (TIME), and perceived intrusiveness (INTR) are called as exogenous variables that predicts the outcome of endogenous variables including online shopping intention (INTT), and ad avoidance (AVDN). Attitude towards PA (ATT) construct is considered as mediating variable as it acts as an mediator to connect REL, TIME, INTR and INT, ADVN (Garson, 2016, p. 20). Mediating variable like ATT is considered as endogenous variable.

Regarding TRA, ATT is proposed to have a theoretical link with its evaluative criteria of REL, TIME, and INTR. As S-O-R theory was applied, this study considers REL, TIME, and INT as the stimulus that trigger the organism of ATT to respond through the targeted behaviours, which are INT, and AVDN.

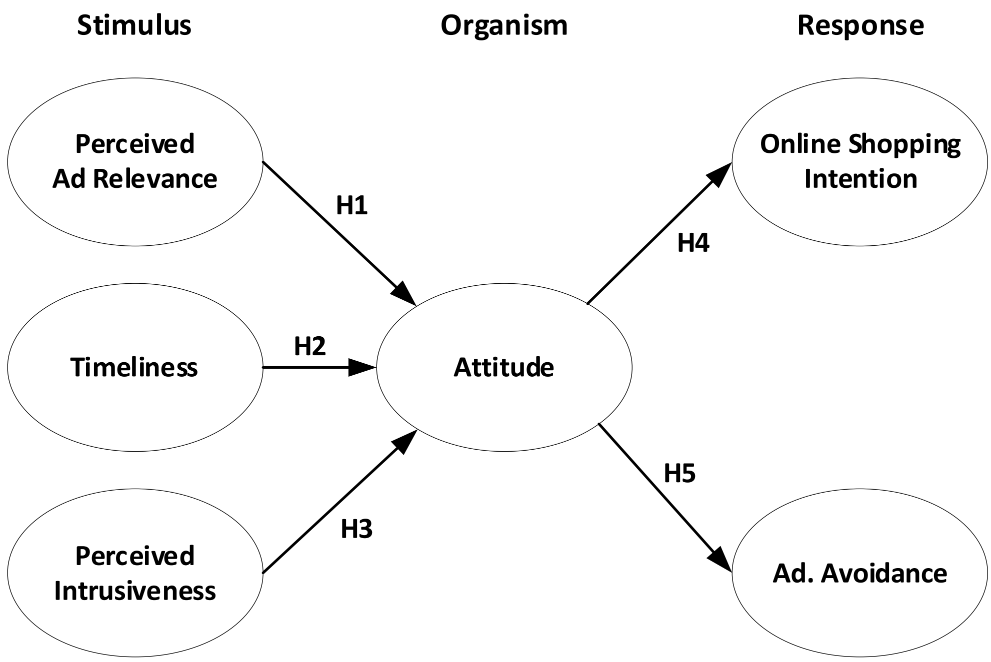

FIGURE 4 Research model

4 METHODOLOGY

This chapter introduce the quantitative research as the selected methodology in this study context. Secondly, data was collected through survey-based method as this data collection strategy is suitable for its effectiveness, and accuracy. Thirdly, questionnaire survey was used to collect quantitative data through well-established questions developed from previous literatures. Lastly, data analysis explains how data is analysed to draw meaningful results.

4.1 Quantitative research

As being defined, research as its core nature is to explore the truth (Hair et al., 2015, p. 3) by setting up a clear purpose, systematically collecting data to achieve the predetermined purpose, and systematically interpreting them into meaningful results (Saunders et al., 2019, p. 4). Business and management research, therefore, is aimed to explore truth related to business phenomena (Hair et al., 2015, p. 4). It is enable to harvest new understandings by combining transdisciplinary knowledge including sociology, psychology, and economics (Saunders et al., 2019, p. 6). The business research process starts by locating the studied topic within a specific research paradigm (O'Gorman & MacIntosh, 2015) followed by literature review, designing the research, data collection, data analysis (Saunders et al., 2019, p. 11). In literature review, relevant theories are gathered to provide the bridge between current research questions and prior knowledge (Hair et al., 2015, p. 43). Research design, on the other hand, focuses on structuring a framework for data collection and analysis (Hair et al., 2015, p. 31).

Quantitative is one of the methodologies applied in designing research. It is distinguished from qualitative methodology as a collection of numerical data through survey, graphs, or statistics instead of non-numerical data collected in qualitative research approach. Positivism, and deductive approach are exclusively linked to quantitative research designs. (Bryman & Bell, 2015, p. 160, Saunders et al., 2019, pp. 176–177; Taheri et al., 2015, p. 155). Deductive approach aims to test a proposed hypothesis by deriving a proof or using evidence from previous literatures (O'Gorman & MacIntosh, 2015, p. 54). Quantitative studies are also classified as a process of quantifying research questions through measurable variables. This is one of main characteristics of quantitative research seeking to examine the relationship among variables with the employment of statistical tools and visualization techniques.

The process of quantitative research includes stages that are put in a linear and successional order (Bryman & Bell, 2015, p. 160). In quantitative research, designing a set of dependent and independent variables is a irreplaceable part of data design. Dependent variable means a variable that can be influenced by another variable. Meanwhile, independent variable is proposed to influence dependent variable. These variables are obtained from research questions and literature review. It is highlighted that a selection and measurement of dependent variables play vigorous role in quantitative research as its relevance significantly affects the final outcomes. (Taheri et al., 2015, p. 157). After identifying dependent and independent variables involved in the research, data collection process starts. Data collection in quantitative research can be executed by either one or more techniques. A single data collection technique is called as mono method quantitative study, which is widely known as survey. (Saunders et al., 2019, p. 178).

It can be observed that quantitative methodology has been applied in various consumer behaviour and attitude studies due to its ability to explain causal relationships between variables. Since quantitative methodology focuses on answering "why" question (Bryman & Bell, 2015), it is suitable to apply in this study context, which aims to understand why consumers perform particular behaviours after seeing the PA-enabled advertisements. Especially, the study seeks to gain an understanding of the causal relationship between PA-enabled advertisements such as its relevance, timeliness and intrusiveness and consumers attitude that leads to their behaviour in purchase intention and ad avoidance.

In addition, quantitative study is conducted a deductive manner, which means that prior theories related consumer attitude and programmatic advertising are found to provide a framework for constructing hypotheses. Furthermore, data is collected through a single method as survey before being statistically measured to test the proposed hypotheses. Finally, a general conclusion can be drawn from statistical results before being interpreted into actional outcomes. Although subjective interpretation has been criticized as quantitative method's drawback (Bryman & Bell, 2015), it is outweighed by its capability to provide various comparable findings, high speed in data collection, more precise answers based on numerical results. (Taheri et al., 2015, p. 155), and repeatability (Bryman & Bell, 2015).

4.2 Data collection

This study employs survey as its method to collect research data as survey is a commonly used method in quantitative research (Hair et al., 2015, p. 218; Saunders et al., 2019, p. 178). Survey is descriptive as it seeks to describe the current state of affair (Kothari, 2004, p. 2). Through survey, the utilization the natural differences in dependent and independent variables and connections among these variables are exploited. It is a structured method that effectively collects significant number of responses through a same set of questions. Moreover, thanks to the uniformed answers collected, data can be easily stored and quantified. (Taheri et al., 2015, p. 165). Therefore, it is cost effective, and has low level of bias (Kothari, 2004, p. 55) as interviewers' has no interference during responding process (Hair et al., 2015, p. 35). Survey method seeks to collect information regarding respondents' behaviour, attitudes, lifestyle, beliefs, expectations, and others (Hair et al., 2015, p. 35; Taheri et al., 2015, p. 165), which are considered as primary data (Hair et al., 2015, p. 218).

Despite its potential, survey as data collection method poses drawbacks. Firstly, respondents' answers can be influenced by their awareness that their attitude or behaviour is being collected. Thus, this may lead to response bias in providing untrue information or someone else answered the survey (Hair et al., 2015, p. 218). Secondly, as respondents administer the responses on their own, they may have less motivation to complete the survey, which may generate low response rate. Furthermore, missing data can happen when respondents skipped the questions due to lack of understanding or technical-related issues (Taheri et al., 2015, p. 166). Acknowledging that survey method has both pros and cons, it is suitable for data collection strategy in this study.

The term survey or questionnaire are often interchangeably used even though researchers emphasize survey as a method and questionnaire as a written form of data collection method or survey instrument (Taheri et al., 2015, p. 165). Structured questionnaire is used in self-completion survey, where the presence of interviewers is omitted (Hair et al., 2015, p. 220). Structured questionnaires are applied to gather large number of quantitative data effectively and conveniently. Data collected is considered as primary data, which is composed through a set of predetermined questions. These questions are adopted from previous literatures and research. Selecting appropriate wording in questionnaire design is important in providing accurate responses. (Hair et al., 2015, p. 220). Because of the interviewers' absence in responding process, it is important to ensure that the respondents thoroughly understand every question to respond accordingly.

Despite the pros and cons of survey, this study finds the survey strategy appropriate in the context of this study. Hence, a digital self-completion survey method as online questionnaire to collect quantitative data. The questionnaire was designed following six steps suggested by Taheri et al., (2015, p.165). After defining the conceptual framework, a list of required information in the survey was composed prior to select the questionnaire method to gather data. Consequently, a draft questionnaire was made to exam its sequential formation, precision, and readability to minimize problems occurring during the response process. Online questionnaire questions are derived from previous studies regarding consumer attitudes, online shopping intention, avoidance of online advertising, ad relevance, timeliness, intrusiveness in online display ads context.

The survey was designed with Webropol Survey & Reporting, which is credited as user-friendly for both interviewers and respondents. After that, it was tested by a small group including the author to identify potential difficulties in answering the questions. Amendment was made to improve the logical and visual effects of the questionnaire. After being designed and tested, the digital questionnaire was sent out at in March 2023 via email to personnels and students of Jyväskylä University. Besides, the survey link was directly sent and shared via Facebook groups, and LinkedIn. It is estimated to take 5 minutes to answer the survey questions. Online users, regardless location, can participate in answering. The survey was open for one month, during which 112 responses were collected.

4.3 The questionnaire

This study employed structured questionnaire to collect numerical data. Questionnaire questions are adopted from previous studies with reliable and validated scales. The questionnaire language is English, included six parts consisting of 31 questions, among which 25 questions were related to the conceptual framework and 6 questions were aimed to gather respondents' background. The main goal of a questionnaire is to deliver the research objectives in a structural and sequential manner to encourage respondents to answer (O'Gorman & MacIntosh, 2015, p. 167). Therefore, this study's questionnaire starts with a brief introduction about the topic followed by questions related to participants' background information and studied constructs. Questions were designed as closed-ended with multiple choice formats; and were put in sequential order in accordance with the research model. Questions related to literatures and theories are compulsory except demographical ones to increase the participation's willingness to answer.

As mentioned previously, PA-enabled ads are rooted from online display ads, whose studied characteristics include relevant, timeliness, and intrusiveness Thus, the questionnaire focuses on participant's targeted behaviour towards display ads resulted from the ads characteristics. Respondents are provided a scenario of their previously ads that were shown after they inserted keywords in the search bar. The scenario is given as follows "Try to remember the last time when you searched for a particular product or service either you completed the search or not. Later, when you surfed the internet for something else not related to the search, that ad popped up." After respondents opened a survey link, a brief introduction about the author, programmatic advertising as the research topic, retailing and consumer behaviour as the study context, and the questionnaire's purpose were represented. More importantly, as the survey was conducted online, anonymity and data privacy were concisely mentioned as "After completing the thesis project, all the collected answers will be disposed of permanently, and no response will be saved in any form on any storage media." In the next page, questions regarding participants' online shopping frequency, ad avoidance, and tendency to purchase products displayed by the ads were asked. This aims to gain a general understanding of a respondent's online shopping background, which is likely helping to explain their attitudes towards display ads.

The second part of the questionnaire focused on the constructs of this study as shown in table 1. The constructs include perceived ad relevance (REL), perceived timeliness (TIME), perceived intrusiveness (INTR), attitude towards PA (ATT), online shopping intention (INT), and ad avoidance (AVDN). All the constructs were adopted from previous studies. Likert's 5-point scale was applied to measure the studied variables ranging from strongly disagree (1) to strongly agree (5). The first construct intended to discover participants' perceived relevance of displayed ads, which were adopted from Jung (2017). Consumers consider an ad is relevant when it is able to fulfil consumers' needs, goals, or values (Jung, 2017). Thus, questions in this construct focused on these factors such as "the ad provided relevant product information to me", "the ad was relevant to my needs", and "the ad was of value to me". The second construct, which was derived from Feng et al., (2016), measured the influential role of timely manner in the context of online display ads (e.g., "[…] timely provided information", "[…] related to a specific time or date", "[…] good source of up-to-date information", "I value this real-time info and interaction that this service makes possible").

The third construct measured consumers' perception about ad intrusiveness. Questions belonging to this construct was adopted from Lee and Hong, (2016) studying consumer's perceived intrusiveness in social media context (e.g., "[…] distract my attention", "[…] hindered my reading", "[…] interfered with me"). Attitude towards ads was the fourth construct, which questions were endorsed from Lin and Kim, (2016) such as "I liked the ad", "I referred the ad", "The ad was very valuable for me". Online shopping intention items derived from Anubha and Jain (2022) was the fifth construct. Its scales included three levels of purchase intention such as very likely/ will definitely/ will purchase. Lastly, the scales for ad avoidance were adopted from Bang et al., (2018) that described consumer's avoidance action and attitude as "click away from the webpage", "hated the ad", "intentionally did not put eyes on the ad", "did not want to click on the ad", "intentionally did not pay attention to the ad", "scrolled up or down to avoid the ad", "intentionally ignored the ad", "wanted to close the webpage", and prefer that "the ads were not on the webpage". The list of constructs and question items are presented in Appendix 3.

TABLE 1 Measured constructs

Construct	**Adopted from**
Perceived ad relevance (REL)	Jung (2017)
Perceived timeliness (TIME)	Feng et al., (2016)
Perceived ad intrusiveness (INTR)	Lee and Hong (2016)
Attitude towards PA (ATT)	Lin and Kim, (2016)
Online shopping intention (INT)	Anubba and Jain (2022)
Ad avoidance (AVDN)	Bang et al., (2018)

The last session of the questionnaire focused on exploring participants sociodemographic information regarding gender, age, and profession.

4.4 Data analysis

In quantitative research, data analysis starts with a conceptual framework and proposed hypothesis review followed by data preparation, determination of descriptive analysis participation, analysis conduction, and evaluation of findings (Hair et al., 2015, p. 350).

Firstly, the conceptual framework and proposed hypotheses were revised for variables and constructs check. Secondly, the collected data was prepared for analyzation by removing uncompleted responses. As all the questions regarding respondents' online shopping background and constructs were compulsory, no missing data was found. Thirdly, descriptive statistics were employed to acknowledging respondents' demographic background and past online behaviour. This can help with data interpretation. Collected responses were coded as numeric to enable statistical software to read easily. Questions related to REL were renamed as REL1, REL2, REL3, accordingly and timeliness questions were TIME1, TIME2, TIME3, TIME4.

Fourthly, after the data was cleaned and coded in a machine-readable manner, it was transferred to IBM SPSS Statistics, a well-recognized statistics software, is best known for its ability to comprehensively run descriptive analysis (*IBM SPSS Statistics*, n.d.). IBM SPSS Statistics helped to analyse descriptive data regarding gender, age, and professions in this study. After that, an exploratory factor analysis was conducted to compose a smaller set of variables due to a large number of original variables set. Moreover, PLS-SEM was employed as it supports the prediction of complicated relationships between constructs regardless of not-normally distributed variables and small sample size, and its popularity in business disciplines research (Hair et al., 2013, 2014). Smart-PLS software with version 4 4.0.9.2 was used to analyse the measurement and structural model of the constructs.

PLS-SEM is a variance-based statistical technique. Partial least square (PLS) is a statistical estimation procedure measuring simultaneous equations' systems. These systems are known as structural equations modelling (SEM). Its purpose is to examine the complex interrelationships between dependent and independent variables. (Hair et al., 2015, p. 457). Consequently, its results help to confirm the hypotheses. Structural equation models (SEMs) has been increasingly employed in studying behavioural science owing to its flexibility to examine complex associations, use of various data type, ability to compare different alternative models (Wolf et al., 2013) regardless of sample size and minimal amount of missing values (Hair et al., 2015, p. 458). PLS-SEM consists of structural and measurement models or inner and outer models, respectively. Structural model refers the constructs and the relationship between them. On the other hand, measurement model represents the relationship between the constructs and their indicators. In other words, measurement model evaluates the consistency, reliability and validity of the constructs while structural model measures the hypothesis (Hair et al., 2015, p. 446). Finally, statistical findings were evaluated to drive meaningful conclusion.

4.5 Common method variance (CMV)

Common biases can occur in survey-based data collection, especially in behavioural research. Hence, it is crucial to apply common method variance (CMV) to prevent biases in final outcomes. CMV is influenced by multiple factors as the survey measurement process, social desirability, and contextual effect of the survey items. (Podsakoff et al., 2003). In other to mitigate the probability of common biases, the questionnaire introduction concisely clarifies the questionnaire's main points to well acknowledge respondents about the study. Besides, the questionnaire was designed so that regardless of responding time, location, and used devices, respondents can easily access and answer questions. Moreover, simple scales were used to avoid misunderstanding.

In addition, respondents can perceive two latent variables measure the same construct, which can negatively affect the research results. Therefore, to address this issue, a lateral collinearity was conducted to validate the collinearity of the gathered data set. Lateral collinearity refers to the perception that predictor variable is the same with the criterion variables. In other word, the observed variables are the same with the construct. By confirming the noncollinearity between indicators and corresponding constructs, misleading results can be prevented. (Kock & Lynn, 2012). The collinearity test was run through SmartPLS software showing the VIF values of all the indicators are lower than the threshold of 3.3. Consequently, it can be concluded that there is no existence of collinearity among the variables.

5 RESULTS AND ANALYSIS

In this chapter, collected data from the online survey will be analysed. Firstly, demographic and background information of the respondents is extracted. In addition, SmartPLS, a statistical software specializing in variance-based structural equation modelling (SEM), was used to measure the measurement and structural models of the study. The results of measurement and structural model are discussed in the second and third part of this section, correspondingly.

5.1 Demographic and background information

Within one month, 100 out of 112 responses were validly collected via Webropol Survey & Reporting, which meets the required sample size for conducting meaningful statistical examination (Hair et al., 2015; Reio & Shuck, 2015; Wolf et al., 2013, p. 458). Invalid data could be resulted from technical-related issues happening during respondents answered the survey such as interruption in Internet or used devices. Therefore, this abandoned respondents to complete the survey. In addition, demographic questions were not mandatory, respondents can skip these questions if they feel uncomfortable in answering them.

Table 2 shows that the survey gathered 35 responses from males, while female respondents was 64, which accounts for 35.4% and 64.6% of the respondents, respectively. Regarding age group, the survey collected highest number of responses from people belonging to 24-29 years old group, which accounts for 52% of the respondents. The second and third biggest age groups were those 18-23- and 30-35-years old accounting for 19% and 15%, respectively. Respondents, whose age ranges from 36-41 years, was the smallest group (6%) while more than 41 years old group contributed 8% of the respondents. In terms of professional background, 49% of respondents were student while respondents who had a job were 42%. Moreover, respondents who did not have a job contributed 5% of the respondents, followed by people with other professions with 3%. Among respondents, retiree accounted for 1%.

Regarding information about consumer's past online purchase and avoiding ads, purchasing online product less than once a month was the most popular answer in the collected data with 41 responses (41%). The least popular answer was purchasing online once a month, which was answered by 25 respondents (25%). Meanwhile, respondents had purchased online products more than once a month accounting to 34% of the respondents. In terms of prior experience in avoiding online display ad and online purchase intention, respondents answered yes made up of 88% and 86% of the respondents, respectively.

TABLE 2 Demographics of the participants (N=100).

Variables	Cases	Percentage
Gender		
Male	35	35.4%
Female	64	64.6%
Other	0	0.0%
Total	99	100.0%
Age		
18-23	19	19.0%
24-29	52	52.0%
30-35	15	15.0%
36-41	6	6.0%
>41	8	8.0%
Total	100	100.0%
Profession		
Employed	42	42.0%
Unemployed	5	5.0%
Student	49	49.0%
Military	0	0.0%
Retired	1	1.0%
Other	3	3.0%
Total	100	100.0%
Online purchase frequency		
Less than once a month	41	41.0%
Once a month	25	25.0%
More than once a month	34	34.0%
	100	100.0%
Prior online ad avoidance		
Yes	88	88.0%
No	12	12.0%
	100	100.0%
Prior online purchase intention		
Yes	86	86.0%
No	14	14.0%
	100	100.0%

5.2 Measurement model

The measurement model is evaluated after the path model is well established. A path model plays a critical role in connecting all the variables and constructs based on the studied theories. (Hair et al., 2014). In this study, a formative path model was used as each indicator characterizes a dimension of the latent variable. (Garson, 2016, p. 17). Formative path model is illustrated by the arrow direction pointing to the latent variables from the indicators.

Evaluating the measurement model or outer model is the first step in examining PLS-SEM results (Hair et al., 2014) to ensure the accuracy of the constructs. The measurement model evaluates the relationship between indicator variables and their subsequent constructs (Hair et al., 2014). As suggested by Hair et al., (2013, 2014), the reliability and validity of the construct in formative measurement model should be verified. Hence, the study examined the item's internal consistency and scale reliability via SmartPLS 4. 4.0.9.2.

Firstly, the measured constructs' internal consistency reliability was evaluated by composite reliability. Composite reliability assists differences in indicator loadings and prevent underestimation of internal consistency reliability (Hair et al., 2014). As shown by the result, all the constructs have composite reliability valued between 0.70 and 0.90 demonstrating satisfactory to good levels of reliability (Hair et al., 2018). Secondly, the indicator loadings were examined. The result showed all the items, except INTR2 (0.685) and AVDN1 (0.601), had loading more than the recommended threshold of 0.708 (Hair et al., 2018), which indicated that all the items have acceptable reliability. Besides, all factor loadings' significance and relevance were evaluated via bootstrapping. As being observed, all the indicator outer loadings were statistically significant (p value <0.01) and related to each other. Moreover, all the indicators' weights ranged from 0 to 1, which revealed positive relationships among them. As a result, the model's formative indicators were statistically significant and positively related to each other. Table 3 shows the list of items, its factor loading, mean, and standard deviation.

Thirdly, the model's validity was examined by observing convergent validity and discriminant validity. Convergent validity refers to the explained variance of a construct's items. Convergent validity metrics was assessed by extracted average variance (AVE). All the construct's AVE values, ranging from 0.594 to 0.806, were higher than 0.50 representing that the construct explains at least 50 per cent of the variance of its items (Hair et al., 2018). Besides, discriminate validity was evaluated to ensure the distinction between constructs. Heterotrait-monotrait (HTMT) ratio was applied to evaluate the model's discriminant validity (Henseler et al., 2015). The result showed that all the HTMT ratio values were below 0.85 implying that the HTMT criterion detected the nonexistence of collinearity problems among the constructs (TABLE 4). Therefore, the measurement model's convergent and discriminant validity were achieved.

In conclusion, the measurement model has strong internal consistency, and good validity so that it can create reliable results. (Hair et al., 2018).

TABLE 3 List of items, factor loadings, mean, and Std deviation.

Construct	Items	Loadings	Mean	Std deviation
Perceived ad relevance (REL)	REL1	0.773	3.190	1.120
	REL2	0.894	3.180	1.099
	REL3	0.921	2.810	1.222
Perceived timeliness (TIME)	TME1	0.722	3.110	1.165
	TME2	0.790	2.880	1.259
	TME3	0.783	2.930	1.219
	TME4	0.786	2.990	1.082
Perceived intrusiveness (INTR)	INTR1	0.892	3.460	1.212
	INTR2	0.685	3.180	1.314
	INTR3	0.875	3.160	1.172
Attitude towards PA (ATT)	ATT1	0.887	2.600	1.192
	ATT2	0.885	2.320	1.256
	ATT3	0.921	2.410	1.114
Online shopping intention (INT)	INT1	0.899	2.560	1.033
	INT2	0.917	2.450	1.203
	INT3	0.824	2.830	1.209
Ad avoidance (AVDN)	AVDN1	0.601	2.940	1.279
	AVDN2	0.843	3.110	1.435
	AVDN3	0.828	3.110	1.370
	AVDN4	0.844	3.360	1.300
	AVDN5	0.872	3.460	1.307
	AVDN7	0.907	3.390	1.363
	AVDN8	0.828	3.240	1.320
	AVDN9	0.885	2.990	1.315

TABLE 4 Composite reliability (CR), Average value extracted (AVE), Heterotrait-monotrait (HTMT).

Construct	CR	AVE	1	2	3	4	5
REL (1)	0.899	0.748					
TIME (2)	0.854	0.594	0.651				
INTR (3)	0.861	0.677	0.105	0.187			
ATT (4)	0.926	0.806	0.601	0.569	0.234		
INT (5)	0.912	0.777	0.695	0.677	0.171	0.778	
AVDN (6)	0.951	0.686	0.178	0.102	0.543	0.480	0.328

5.3 Structural model

Structural model, or inner model, assesses the proposed relationship between hypotheses. The quality of structural model is examined based on its prediction ability of the endogenous constructs. (Hair et al., 2014).

Regarding structural model's results, the first hypothesis proposing that ad relevance has positive relationship on attitude towards PA is supported (β = 0.356, p < 0.01). Therefore, *H1* is accepted. The results also confirm the positive relationship between TIME and ATT (β = 0.325, p < 0.01). hence, *H2* is accepted. H3 proposes that perceived ad intrusiveness negatively relate to consumer's attitude. This is confirmed in the structural model results (β = -0.265, p < 0.01). Regarding the impact of attitude towards online purchase proposed by *H4*, the results demonstrate that attitude positively affects consumer's intention to online shopping (β = 0.677, p < 0.01). Hence, *H4* is accepted. Moreover, *H5* states that consumer's attitude toward PA exhibits a negative relation with ad avoidance behaviour. This relationship is confirmed by the results (β = -0.449, p < 0.01). Therefore, *H5* is confirmed. Figure 5 represents the study's results of path model.

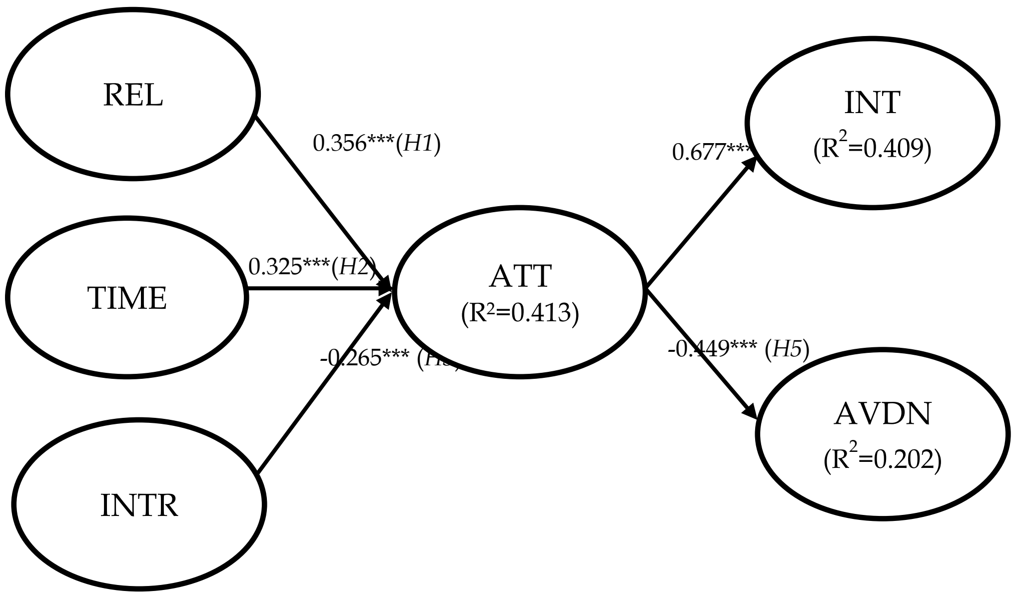

FIGURE 5 Path model

6 DISCUSSION AND CONCLUSION

In this master's thesis the focus was on consumer's attitude towards PA-enabled advertisements, which leads to their target behaviour of purchase intention and ad avoidance. Based on TRA and SOR, the study developed 5 hypotheses by collecting data via online questionnaire. Theoretical and managerial implications are mentioned prior to limitation and room for future research.

6.1 Theoretical contribution

Consumer attitudes has never been an outdated topic. In business disciplines, especially marketing, there are numerous research about consumers' attitudes toward targeted behaviour in social media, sponsored search, in-game marketing, ecommerce, to name a few. However, there is dearth studies about consumer's behaviour in the context of programmatic advertising. Moreover, previous research mainly explores PA from the computational perspectives or from the business-to-business point of view. Hence, this study looks at PA from consumer's perspective to understand how ads served by PA technology can influence consumer's attitudes and subsequently motivate them to perform the studied behaviours, which are intention to purchase and ad avoidance.

Through prior studies, it has been verified that ads created by AI-empowered technology as part of PA have gained its popularity among marketers due to its high personalization, and timeliness (Ciuchita et al., 2022; Zhang et al., 2020). Through AI technology, ads are produced based on consumer data collected via embedded cookies prior to deliver it to the target consumers (Gao & Liu, 2022) in a timely manner (Chen et al., 2022; Choi et al., 2020). From consumer's perspective, ads that are highly personalized and displayed in a timely fashion are considered as relevant and valuable (Hühn et al., 2017). They are timesaving, and effective in providing useful information in products seeking process. Ads that are shown up in a timely manner can also assist consumers in making appropriate decisions (Huh & Faber, 2022; Samuel et al., 2021). In contrast, consumers perceive the ad is intrusive due to its high level of personalization and content obstruction. When the ads are displayed more frequently, it obstructs consumer's online activities such as reading the initial content on the website. As a result, it developed irritation leading to intrusive perception.

Furthermore, prior studies have shown that there is a positive connection between consumers' attitudes and purchase intention (Anubha & Jain, 2022; Ciuchita et al., 2022; Duffett, 2015; Sebastian et al., 2021; Zhang et al., 2020). When a consumer has positive attitude towards the displayed ads, they are more likely to click on the ad, which is considered as the first stage of the buying process (Aiolfi et al., 2021). In contrast, a negative attitude towards the ads such as high level of perceived intrusiveness will negatively influence consumer's behaviour towards that ad. This can lead to ad avoidance including ignoring the ad, or even clicking away from the webpage (Bang et al., 2018)

Due to the forementioned points, this study presents perceived ad relevance (REL), timeliness (TIME), and intrusiveness (INTR) as determinants of consumers' attitudes towards PA (ATT), which triggers their performance of purchase intention (INT) and ad avoidance (AVDN). In short, this study explores consumer's attitude towards PA in the context of online shopping. The results show that all the proposed hypotheses are statistically significant (*t*-value > 1.96 for two-tailed test and $p < 0.001$). Among the variables, REL has the strongest significance to ATT while ATT has the strongest significance to INT.

The study findings contribute to the literature on consumer's attitudes towards PA-enabled ads in retailing context. The results showed that the relationship between ATT and REL is positive and significant. This is in line with Ciuchita et al., (2022) and their findings. Regarding the effect of timeliness on consumer's attitudes, the results confirm the positive and significant relationship between TIME and ATT, which was verified by Zhang et al., (2020). Besides, INTR has proven to have negative relationship with ATT through studies conducted by Zhang et al., (2020) and Samuel et al., (2021). The findings strengthen this relationship.

In addition, the study finds that ATT positively and significantly influences INT. This result expands the findings of Aiolfi et al., (2021), Zhang et al., (2020) and Ciuchita et al., (2022), where the authors focused on finding the positive impact of ATT to click intention, and attitude towards retailers. Hence, the present study explores the ATT and consumer buying intention, which contributes a wider aspect of ATT toward targeted intention. Furthermore, the results show the statistically significant and negative relationship between ATT and AVDN. This reinforces and extends the study of Dodoo & Wen (2019). In their study, Doo & Wen (2019) focuses on the direct relationship between REL and AVDN cognitively, effectively, and behaviourally. This study, on the other hand, looks at ad avoidance target performed behaviour at general level rather than exploring it in three different spectrums.

In conclusion, reflected by this study results, attitudes play a crucial role in mediating the relationship between REL, TIME, INTR and INT, AVND. Compared to previous studies, this study has been so far the first one to study the meditating role of ATT in this connection. This helps to explain how consumer attitudes can meditate the relationship between triggered elements and targeted behaviours. In the other words, the study explains how different studied elements can lead to targeted behaviour by influencing attitudinal perspective. More importantly, this study results also bring to light the direct relationship between consumer attitudes and ad avoidance, which has not been observed in prior studies. The hypothesis testing is summarized in table 5.

TABLE 5 Hypotheses testing

	T value	Hypotheses test
H1: Relevance -> Attitude	3.976***	Supported
H2: Timeliness -> Attitude	3.741***	Supported
H3: Intrusiveness -> Attitude	2.940**	Supported
H4: Attitude -> Purchase intention	9.471***	Supported
H5: Attitude -> Ad avoidance	5.913***	Supported

Note: **p<0.01; ***p<0.001 (two-tailed)

6.2 Managerial implications

As being observed, most of prior research and literature regarding PA mainly focused on its characteristics, particularly its technical aspect. Meanwhile, research about PA from consumers' point of view has been limited in quantity. Therefore, this present study aims to contribute to the lack of PA research from consumers' angle. Via this study, important consumer's perspectives are brought to light so that marketing personnels and retailers should pay attention when deploying PA-enabled ads.

Programmatic advertising has been gaining tremendous popularity in the field of marketing due to its effectiveness in providing highly related ads to the right target audience at the right time with an optimal cost. It has been proven that, despite consumers' high appreciation of personalized and timely shown ads, they also hold a negative perception towards the ad. Exceeding level of personalization can make consumers think that the ad is intruding their online privacy as the ads are highly related to their utilitarian needs. Besides, ads shown with high level of frequency interferes with a consumer's initial goal for online activities. Thus, it is essential for marketers to be aware of this issue when conducting marketing campaigns to find the balance between relevance and timeliness while mitigate the rising effect of perceived intrusiveness.

Secondly, this study was driven to explore how consumers' attitude affect their behaviour as intention to purchase and avoiding ads. It worths noticing that attitude plays a critical role in motivating consumers to perform the desired actions. By understanding how consumers' attitude is affected and how it affects the determined behaviours supports marketing professionals and retailers in designing good targeting approach. Thus, marketers and retailers are advised to thoroughly analyse determinants of consumers' attitudes in the context of PA-enabled ads to maximize the positiveness in consumers' attitudes.

Thirdly, as publishers control the ads serving and delivery, retailers have very little or no information about how their ads budget is used or where in the webpage it is displayed (Li et al., 2017). As a result, ads are shown on poor quality websites, which strongly affects consumers' attitude and consequently, their behaviour towards the displayed ads (Shehu et al., 2021). In addition, with the help of AI technology, ads are created in a blink of an eye to the target audiences relevantly, and timely. This is prone to brand safety as AI manages the task automatically based on its algorithms. Hence, it is essential for retailers to select reliable publishers whose content is highly related to the ads' context rather than opting for high ad's frequency.

More importantly, despite the hype of PA, not all retailers and marketers fully understand how PA works, without mentioning the fast-evolving environment of PA technology. As PA itself is still evolving; and the application of AI in PA is still immature. Marketers and retailers are advised to first understand thoroughly PA's pros and cons before conducting campaigns via PA-enabled ads and keep updated with the technology development and regulations related to PA to design corresponding marketing strategies.

6.3 Limitations of the study and future research

This study undoubtedly has several limitations. Firstly, the data was collected within Finland in a short period of time. Future research can extend geographically and in longer time to compare the results between respondents from different countries. Secondly, the study tries to establish the relationship between respondents' prior online behaviour background and their current tendency to perform such behaviour. Hence, its demographic was merely placed on prior online purchase frequency, ad avoidance, gender, age, profession without considering respondents' income, which could be a determinant factor motivating online purchase intention. Depending on the purpose of future research, income can be added in the list of respondents' demographical information. Thirdly, the study mainly focuses on the characteristics of PA-enabled ads that trigger targeted behaviour and provides a scenario based on respondent's previous experience. Therefore, future research in the same topic could focus mainly on one ad that can be compared to this. Fourthly, the study focuses on online purchase intention in accordance with online ads. However, there are cases that consumers are motivated by online displayed ads and intend to buy a product or service at a physical store after seeing the ads. Therefore, future research can establish a relationship between consumers' attitude towards PA-enabled ads and offline purchase intention.

Within the scope of this study, perceived ad relevance, timeliness, and intrusiveness were separately studied as the influencing elements of consumers' attitude. What if these elements are intertwined? Prior research has shown that high level ad relevance leads to high perception of ad intrusiveness. However, this study does not establish the relation between these two factors. Therefore, there is room for future research to look deeper into this issue and compare the effect it has on attitude. Besides, this study concentrates on the characteristics of

PA such as relevant, timeliness in affecting attitude while ignoring users' online intrinsic motivation. Consumers whose online goal is to update information such as news, possess high level of negativism towards the ads that interfere with their goal. On the other hand, consumers who are seeking information about a product, when they see PA ads shown while they are reading news, will consider the ad is useful. This gives room for future research to explore not only the external factors but consumers' intrinsic motivation in affecting their attitude toward the displayed ads.

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APPENDICES

APPENDIX 1: "Studied statistics tables.

A Descriptive statistics of participants' online behavior background (N=100)

Items	Mean	Std. deviation
Frequency	1.93	.868
Ad avoidance	1.12	.327
Online purchase intention	1.14	.349

B Collinearity statistics (VIF) – Inner model

Attitude -> Ad avoidance	1.000
Attitude -> Purchase intention	1.000
Intrusiveness -> Attitude	1.045
Relevance -> Attitude	1.445
Timeliness -> Attitude	1.471

C. F-square - List

Attitude -> Ad avoidance	0.253
Attitude -> Purchase intention	0.848
Intrusiveness -> Attitude	0.114
Relevance -> Attitude	0.150
Timeliness -> Attitude	0.122

D. Descriptive statistics

	Original sample	Sample mean (M)	St. deviation	T-value	P-value
Attitude -> Ad avoidance	-0.449	-0.455	0.076	5.913	0.000
Attitude -> Purchase intention	0.677	0.681	0.072	9.417	0.000
Intrusiveness -> Attitude	-0.265	-0.270	0.090	2.940	0.003
Relevance -> Attitude	0.356	0.356	0.909	3.976	0.000
Timeliness -> Attitude	0.325	0.328	0.087	3.741	0.000

APPENDIX 2: "Constructs and question items"

Constructs	Questions
Perceived ad relevant (REL) Jung (2017)	REL1: The ad provided relevant product information to me. REL2: The ad was relevant to my needs. REL3: The ad was of value to me.
Perceived timeliness (TIME) Feng et al., (2016)	TIME1: The ad provides timely information. TIME2: I would view the ad related to a specific time or date (eg. anniversary, changes in stock prices) as useful TIME3: The ad is a good source of up-to-date information. TIME4: I value this real-time information and interaction that this service makes possible.
Perceived ad intrusiveness (INTR) Lee and Hong (2016)	INTR1: The ad distracted my attention. INTR2: The ad hindered my reading. INTR3: The ad interfered with me.
Attitude towards PA (ATT) Lin and Kim (2016)	ATT1: I liked the advertisement. ATT2: I referred the advertisement. ATT3: I think the advertisement was very valuable.
Online purchase intention (INT) Anubba and Jain (2022)	INT1: It is very likely that I will purchase the brand advertised. INT2: I will definitely try the brand advertised. INT3: I will purchase the brand advertised next time I need this.
Ad avoidance (AVDN) Bang et al., (2016)	AVND1: I wanted to click away from the webpage. AVND2: I hated the ad on the webpage. AVND3: I intentionally didn't put my eyes on the ad on the webpage. AVND4: I didn't want to click on the ad even if the ad drew my attention. AVND5: It would be better if the ad were not on the webpage. AVND6: I intentionally didn't pay attention to the ad on the webpage. AVND7: I scrolled up or down the webpage to avoid the ad. AVND8: I intentionally ignored the ad on the webpage. AVND9: I wanted to close the webpage to avoid the ad.