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Measuring the advertising value of personalised ads in smartphones based on consumer literacy and privacy concerns

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ABSTRACT

Because of the widespread use of smartphones in everyday life and advances in data analysis technology, brands are increasingly focusing on advertising via smartphone while collecting customer data. Advertisements are made to reach customers through two types of data collection: the first is using customer online behaviour to show personalised ads, which is known as online behavioural advertising (OBA), and the second is hearing out customer media usage and providing personalised ads, which is known as synced advertising (SA). The question here is whether personalised ads are useful and project a positive image to customers, which are reliable. The purpose of this paper is to provide a knowledge of how OBA and SA work and why it is vital to address personalised adverts in smartphones that are powered by AI algorithms due to privacy concerns. The purpose of this empirical investigation is to determine is purchase intention is accelerated based on the advertising value of personalised adverts, their literacy, and privacy concerns and to test the effect of personalised advertisement value on purchase intention.

Keywords – Online Behavioural Advertising (OBA), Synced Advertising (SA), Smartphone, Advertising value, Privacy concern, Purchase Intention

1.INTRODUCTION

With the widespread use of smartphones for daily activities, advertisers target consumers via smartphone. In this internet world, there is no concern for people in need of personal assistance, but there is concern on people as consumers about their activity for their data, as it is critically important for brands to target you with personalised ads. Personalised ads are targeted towards consumer using artificial intelligence algorithm to collect data from consumers which can be used for , there are two kinds of advertising which is common now in personalising ads to consumer they are online behavioural advertising (OBA) and synced advertising (SA). OBA is defined as the technique of tracking people's online activities and utilising that data to display them individually tailored adverts. Web surfing data, search histories, media consumption data , app use data, purchases, ad click-through reactions, and communication content, such as what individuals write in e-mails or post on social networking sites, are all examples of online activity. Data of online activity is often collected through cookies. Synced ads are TV synchronised advertising refers to the use of technology to activate digital adverts in real time depending on television content. TV ad synchronisation occurs when demand-side systems combine with real-time audio, video, and metadata recognition. Brands decide the terms and pictures that should activate ad campaigns using demand-side platform technology, which analyses TV programming. When this happens, the digital commercials will be in sync with what has been watched on TV. Watermarking, which is a legal practise, is one technique that is utilised for this. Watermarking is a sound signal embedded in media content that is recognised by a mobile application. Because of various claims made by consumers about mobile eavesdropping of consumer conversations and targeting ads through social media or other platform with smartphone but no strong empirical evidence had been proved for these claims, this paper focuses on examining the impact of this personalised ad in the real world by empirically measuring the purchase intention & Ad value and various literature studies are done to understand whether this

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personalised ads uses legal data and defined procedure to deliver targeted ads and process flow is made for better understanding how this personalised ads work . There are suggestions on how to prevent privacy concerns while using a mobile device. But from the study it is clear that privacy concern does not have any impact on ad value but still privacy concern is an issue among consumer while speaking about personalised ads.

2. REVIEW OF LITERATURE

Claire M. Segijn & Iris van Ooijen,2020 in their study about OBA and SA had identified that Privacy hazards were cited by a big number of customers as expenses of both tailored advertising tactics, followed by intrusiveness, and they expressed unfavourable feelings about personalization strategies. These types of tailored advertising were largely connected with creepiness, which was higher for SA than OBA. This discrepancy might be explained by SA's real-time nature. When customers are targeted with adverts while utilising topic-relevant media, they may get the impression that they are being observed, which can be seen as 'creepy'. They also conclude that there is no literacy about SA among customers which is also a reason for creepiness, Nicholas R.J.Frick & et al,2021 examines about the perceived surveillance of conversation through smart devices and states The belief that smart gadgets surreptitiously record conversations is common, and there is certainly a need for investigation into this phenomena. The dread of being watched should not be dismissed as an urban legend too hastily; it is a genuine issue that is frequently connected with dystopian future scenarios and dictatorial control of institutions and organisations. While the goal of this research is not to determine whether or not people's interactions are monitored, it does give insight into the individual characteristics that influence this notion. Jacob Leon Kroger and Philip,2019 in their study states many consumers fear firms of surreptitiously listening in through their smart phones when internet adverts appeared to react to issues addressed in private face-to-face talks. This research studied the general feasibility and detectability of mobile eavesdropping assaults, as well as current techniques to understanding the phenomena. While it's conceivable that the oddly precise advertising were merely a result of coincidence or traditional profiling methods, the eavesdropping suspicions have yet to be confirmed, either by device manufacturers and ecosystem suppliers or by the research community.

2.1 AI algorithms used in social media and other online platforms

When individuals discuss something, they often say they saw a digital ad for it on social media or another online channel. People believe that social media platforms are listening in on their conversations in order to target advertising at them, but in reality, actively listening to every single discussion, recording it, and keeping it for data processing in order to target ads is exhausting and impractical. Social media platforms employ a set of big data analytics and AI algorithms to track mobile devices and their usage, as well as to locate people who are using them. Because of this algorithm, it is simple for social media to display ads that have been searched by colleagues, friends, or family members who are in close proximity. For example, if a co-worker searches for a bag and discusses it with another colleague, it is feasible that another colleague would see bag advertising on social media or another online platform without searching for it due to such algorithms. This happens because, whether we're offline or online, certain social networking programmes run in the background if the user has given third-party cookies permission which are actually marketing agencies. AI algorithms can assist this marketers in constructing people's complete social networks by rating individuals around them depending on how much they care about or engage with them. They can then begin to target consumers with adverts based on data obtained from friends and family members who are also using the same platforms. This is why individuals get present suggestions from their friends or family when they have a birthday, and it irritates them since they would have thought about or discussed buying a gift with others.

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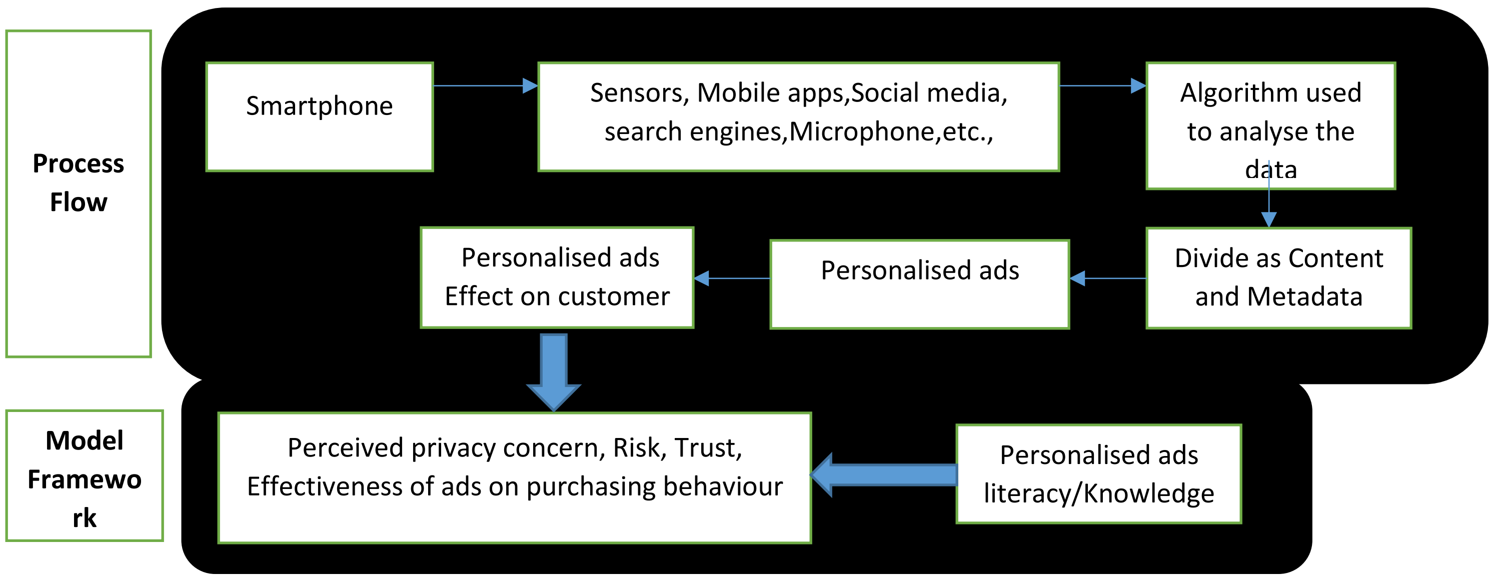
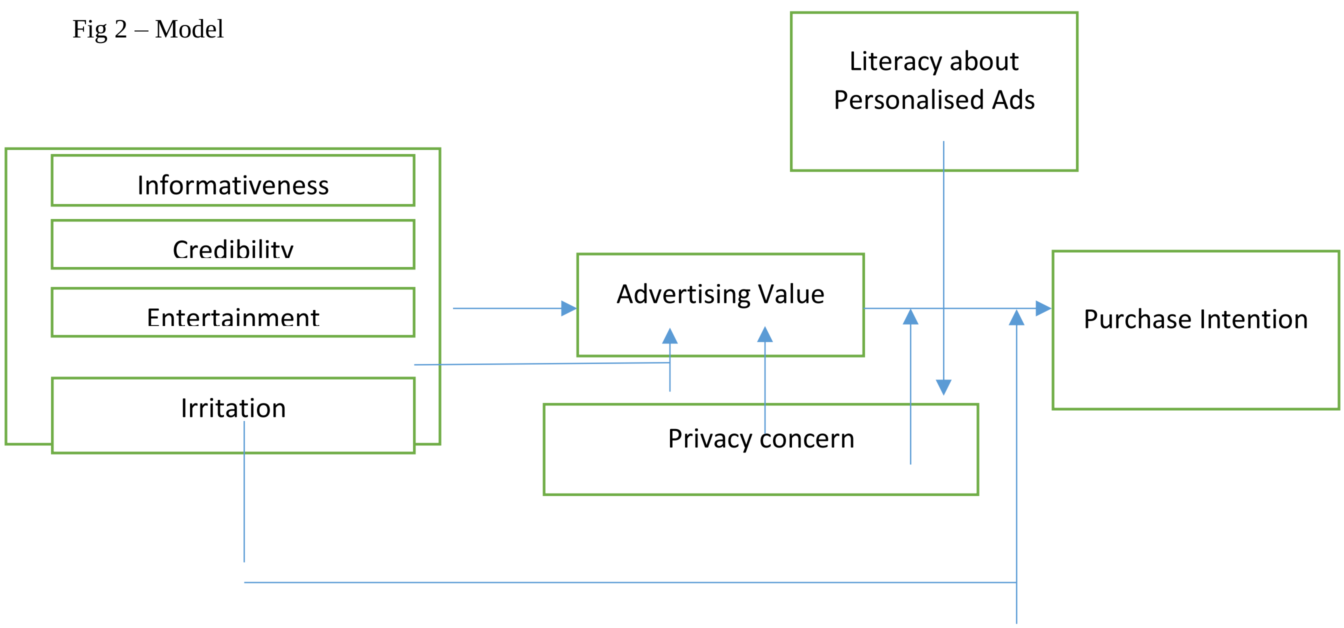
Fig 1 – Process Flow



It is clear in from literature that various sensors, microphone that is embedded in the mobile phone collects data continuously which can be utilised by algorithms to send us personalised ads. Metadata plays a major role in this personalised ads algorithms. Data craft is a group of practises that engage with new computational and algorithmic methods of organising and classification in order to produce, rely on, or even play with the abundance of data on social media, (Acker, A. (2018)).Big data mining and analytics are used by business intelligence which is used for tracking and understanding customer behaviour through which personalised ads are targeted which contains terabytes of collected customer content data and meta data, (Gerdman, T et al,2017).With this techniques personalised ads are targeted to customer and in this study whether this privacy concern or any creepiness or irritation feeling affect the consumer is studied empirically, model is adopted from (Martins J,2018) and privacy concern (Hyejin Kim et al, 2017) and Ad literacy (Segijn, C. M,2021) is introduced from the literature study for measuring Ad value and purchase intention.

Fig 2 – Model



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2.2. RESEARCH QUESTIONS

The research questions (RQs) that emerged are as follows:

RQ1 – What are the factors that influence advertising value of personalised Ad

RQ2 – Do emotions add significance to advertising value in personalised Ad

RQ3 – Does Privacy concern influence Ad Value

RQ4 – Does Ad value of personalised ads influence purchase intention

RQ5 – Does Personalised Ad literacy plays an important role in forming purchase intention in personalised ads?

RQ6 – Does Irritation and Privacy concern will have impact on Purchase intention

2.3 HYPOTHESIS

(H1): Informativeness of Personalised Ads is positively associated with advertising value

(H2): Credibility of Personalised Ads is positively associated with advertising value

(H3): Entertainment of Personalised Ads is positively associated with advertising value

(H4): Irritation of Personalised Ads is negatively associated with advertising value

(H5): Privacy Concern is negatively associated with advertising value

(H6): Perceived advertising value is positively associated with Purchase intention

(H7): Personalised Ad Literacy is positively associated with purchase intention

(H8): Irritation is negatively associated with Purchase intention

(H9): Privacy Concern is negatively associated with purchase intention

3 METHODOLOGY

The data was collected by online survey in tamilnadu. A survey questionnaire was prepared and collected the response using google form. Simple Random sampling was adopted to collect data.104 samples were collected and used for analysis. The measurement items were adapted from existing literatures and previously validated scale. Personalised ads literature were also adapted and tested in this study. The constructs were measured using 5 point Likert scale which ranges from 1 = strongly Agree to 5 = Stongly Disagree. The items Informativeness, Credibility, Entertainment, Irritation and Advertising value were adapted from (Martins J et al.,2018),Privacy concern construct was adapted from literature (Hyejin Kim et al.,2017),Advertisement Literacy (Claire M. Segijn,2022) was used in this study to measure purchase intention effect along with Advertising value. Advertising value effect was measured using Informativeness, Credibility, Entertainment, Irritation (Ducoffe.,1995), (Taanika Arora.,2019) which is used to measure purchase intention.

For those measurement items reliability and validity were tested.Cornbach Alpha of .912 is obtained which shows the strong internal consistent of items and constructs. For each construct Cronbach's alpha is measured and shown in Table 1.Validity of the questionnaire is checked using Pearson correlation coefficient all the obtained questionnaire value are greater than critical value and is highly significant so the questionnaire is valid.

For testing the hypothesis relationships multiple regression analysis is used. Before proceeding with regression analysis normality of the dependent data is analysed and it is shown in Table

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TABLE 1

Factor	Survey Information	Reliability Test Cronbach's Alpha
Informativeness	Informativeness1	.772
	Informatiiveness2	
	Informatiiveness3	
Credibility	Credibility1	.724
	Credibility2	
Entertainment	Entertainment1	.813
	Entertainment2	
Irritation	Irritation1	.800
	Irritation2	
Advalue	Advalue1	.803
	Advalue2	
	Advalue3	
Privacyconcern	Privacyconcern1	.857
	Privacyconcern2	
	Privacyconcern3	
	Privacyconcern4	
	Privacyconcern5	
	Privacyconcern6	
	Privacyconcern7	
Ad Literacy	Ad Literacy1	.802
	Ad Literacy2	
	Ad Literacy3	
Purchase Intention	Purchase Intention1	.787
	Purchase Intention2	
	Purchase Intention3	

Linearity test is done and it is found that data is linear, purchase intention with Ad value and Ad literacy is analysed and found R^2 value is less than obtained R value no data improvement is needed and there is significant linearity between the purchase intention and Ad value likewise Ad literacy is also checked with purchase intention. Advertisement value linearity with Informativeness, Credibility, Entertainment, Irritation and Privacy Concern is also checked and found no data improvement is needed. There is no missing value or any outliers in the data. Homogeneity of the data is checked and it is found that all factor significance value is greater than 0.05 that data is homogenous in nature. Data is tested with multiple regression analysis for testing the hypothesis and to understand about the fitness of model.

4. **Result and Discussion**

4.1 Characteristics of Sample

Simple Random sampling is performed and questionnaire is circulated in google form online survey of 104 respondents were valid respondents and they are utilized for analysis. Equal value of male and female is present and age group is categorized according to generation. Employment and Education details were collected for reference purpose. It is found that respondents group were well educated from the frequency analysis.

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Table 1

Variable	**Classification**	**Frequency**	**Percentage%**
Gender	Male Female	50 54	48.1 51.9
Age	Gen X Millennials Gen Z	4 56 44	3.8 53.8 42.3
Employment	Student Private Government Business other	22 55 4 7 16	21.2 52.9 3.8 6.7 15.4
Education	School UG PG Doctoral No Education	- 48 50 6 -	0 46.2 48.1 5.8 0

4.2 Hypothesis Testing

First personalised Ad value is taken as dependent variable and factors Informativeness, Credibility, Entertainment, Irritation and privacy concern used as independent values as per literature (ducoffe,1995), (Taanika Arora.,2019) thus effects these factor on ad value is tested.

From Regression table 3 it is found that R value is .743 which indicates a high positive correlation. The R^2 value is emphasises how much of total variation in the ad value can be explained by independent variable ,In this case 55.2% of variance can be explained by the independent variables, which is moderate. Also R^2 is used when two or more regression model are compared having the same dependent variable but different independent variables. Durbin Watson D statistics value is used to interpret the autocorrelation between residuals, the obtained D value is for multiple regression is 1.960 which shows there is no autocorrelation. Regarding the goodness of fit, the analysis of variance ANOVA presents strong evidence that factors have a non-zero coefficient and considered fit (F = 24.138,P = 0.000) ,P value is less than 0.005 which indicated that regression model predicts dependent variable well,i,e regression model statistically and significantly predicts the ad value thus model is suitable fit for the data.R^2 value indicating 55.2% of observation were fit for sample regression. The adjusted R^2 result shown in table 3 indicates that Informativeness, Credibility, Entertainment, Irritation and Privacy Concern has 55.2% of variance in the PAV.From table 3, Variance Inflation Factor (VIF) for all constructs were less than 5.0 and Tolerance value ranged between .424 to .818 indicating absence of multicollinearity.

TABLE 2

Model	Unstandardized Coefficient		Standardized Coefficient			Collinearity Statistics	
	B	S.E	Beta	t	Sig.	Tolerance	VIF
Constants	0.289	0.315		0.918	0.361		
Informativeness	.313	.112	0.286	2.789	.006	.424	2.360
Credibility	.289	.109	0.289	2.662	.009	.397	2.520
Entertainment	.265	.091	-0.024	2.892	.005	.458	2.182
Irritation	-.020	.063	0.024	-.317	.752	.818	1.223

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Privacy Concern	.025	.096	.024	.261	.795	.535	1.871
Goodness of Fit	F = 24.138 P= 0.000 $R^{2=}$ .743 Adjusted $R^{2=}$ .552 Durbin Watson = 1.960						
a.Dependent Variable : Personalised Ad Value(PAV)							

From the inference it is understood by the p value Informativeness, Credibility, Entertainment has sig value less than 0.05 which has positively significant effect on personalised ad value.Thus this provides strong statistical evidence that the hypothesis H1, H2 and H3 is supported.It is also evident that irritation and privacy concern had p value greater than 0.05 which proves irritation and privacy concern were not significant predictors of personalised ad value (PAV) therefore H4 and H5 is rejected.

Second we examined the effect on Purchase intention variation with personalised ads using Ad value other moderating variables like Irritation, Privacy concern, Ad literacy is added and analysed using hierarchical linear regression analysis. From the Table 3 it is clear that with personalised Ad value (PAV) accounts for 69.9% in variance of Purchase intention (PI) and in model 2 PAV, Irritation, PAL and PC accounts for 71.1% in variance of PI. It is also statistically evident by adding Irritation, PAL and PC there is addition of 2.3% of variance in PI. In both model considering the P value less than 0.05 the blocks are statistically significant which supports moderating effect is present.

TABLE 3

Model Summaryc									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.836a	.699	.696	.554	.699	237.222	1	102	.000
2	.850b	.723	.711	.540	.023	2.763	3	99	.046
a. Predictors: (Constant), ADV_Total									
b. Predictors: (Constant), ADV_Total, IRR_Total, PAL_Total, PRC_Total									
c. Dependent Variable: PI_Total									

From the table 5 it is clear that there is no multicollinearity and PAV has high positive correlation on PI and PC has significant negative correlation on PI but with negligible coefficient, PAL has significant positive correlation on PI. Irritation does not have any significant effect on PI.Thus hypothesis H6.H7 and H9 is accepted H8 is rejected as per the inference from table 5.It is also proved overall PAV has higher effect on purchase intention.

TABLE 4 - Coefficient

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.375	.150		2.493	.014		
	PAV	.806	.052	.836	15.402	.000	1.000	1.000
2	(Constant)	.321	.233		1.382	.170		
	PAV	.803	.053	.833	15.172	.000	.930	1.075

	PC	-.173	.069	-.173	-2.515	.014	.594	1.683
	IRRITATION	.064	.047	.080	1.372	.173	.828	1.208
	PAL	.129	.056	.149	2.317	.023	.679	1.472

DISCUSSION

From the interpretation it is clear that even though people have concern on privacy issue it is understood it does not have any effect on the advertisement value of personalised ads this is main reason so many brands are preparing personalised ads even though it creates creepiness and irritation among the consumer because it has negligible effect on either advertisement value or purchase intention. The information provided in personalised ads if credible then it is utilised by the consumer for their purchase but still there is need of analysing about privacy because when this kind of ads keep repeating the customer might develop aversion towards the brand which has to be examined further about the repetitiveness of personalised ads and its effect on consumer .It is also evident that advertisement literacy has effect on personalise ads thus informing the customer about personalised ads and increasing literacy of how AI algorithms, OBA and synched ads work to customer is important and it is clearly understood from the study. Privacy concern plays a part when it comes to purchase intention event though it does not affect PAV it has negative effect on purchase intention of consumer event though it is smaller in effect it is really important to consider this part of personalised ads seriously.

CONCLUSION

When not in use, consumers should utilise their phone's privacy settings to turn off the microphone and background programmes, and be cautious about allowing cookies when installing apps or accessing websites. From this study it is clear that advertising value is important so there is necessity in focusing the information, credibility and entertainment aspect before targeting the customer. The major limitation of study is further analysis is needed to understand the irritation creepiness and privacy concern part of personalised ads to come to more conclusive decision. This paper has touched the parts of how personalised ads work, types of personalised Ads and it has analysed purchase intention and Ad value keeping in consideration of privacy issues and creepiness. This paper had analysed empirical side as well process flow is created after reviewing various paper of personalised ads which will help in increasing the literacy of personalised Ads.

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