Library Progress International *Print version ISSN 0970 1052*
Vol.44 No. 3, Jul-Dec 2024: P. 16220-16234 *Online version ISSN 2320 317X*

Original Article *Available online at www.bpasjournals.com*

The Mediator Effect: Exploring Privacy Concern, Perceived Benefit, Personalization and the Repurchase Intentions of AI-fashion retailing Applications

[1]Priyo Das (corresponding author), [2]Dr. Surjyasikha Das, [3]Dr. Rinki Mishra, [4]Dr. Ayan Chakraborty, [5]Anindya Thakur

[1]Research Scholar, JIS University, Department of Management Studies
E-mail: priyodas1996@gmail.com
[2]Assistant Professor and PhD supervisor, JIS University, Department of Management Studies
[3]Assistant Professor and PhD supervisor, Parul University, Faculty of Management Studies
[4]Assistant Professor, JIS University, Education Department
[5]MBA final year student

How to cite this article: Priyo Das, Surjyasikha Das, Rinki Mishra, Ayan Chakraborty, Anindya Thakur (2024) The Mediator Effect: Exploring Privacy Concern, Perceived Benefit, Personalization and the Repurchase Intentions of AI-fashion retailing Applications. *Library Progress International,* 44(3), 16220-16234

Abstract-
This research looks at how customers behave regarding Artificial Intelligence (AI) in fashion retail. We focus on privacy concerns and the perceived advantages of sharing data, as these relate to customers' intentions to buy again. We also explore if personalization helps lessen negative feelings and strengthens this connection. To meet our research goals, we used stratified random sampling to create three different groups based on their experience with apps, income level, and education. We followed set rules for sample size and gathered responses from 252 participants. For data analysis, we used Factor Analysis and Structural Equation Modeling. The results were surprising. Our analysis shows that privacy concerns do not negatively affect customers' intentions to repurchase. In fact, both perceived benefits and personalization have strong positive effects on these intentions. However, we cannot clearly determine if privacy concerns influence customers positively, which suggests the need for more research. This study offers a new way to understand customer behavior toward AI in fashion retail by using Privacy Calculus Theory. We included personalization as a key motivating factor, recognizing its importance for customers when they use apps. This adds a valuable perspective to our research. Additionally, we examine how privacy concerns and perceived benefits affect personalization in the context of AI in fashion retailing..
Keywords- Artificial Intelligence, AI-fashion retailing, Customer reuse intention, Privacy Calculus Theory.

Introduction-

Artificial intelligence (AI) is contributing a shift towards a more algorithmic society (Shankar, 2018). Advancements in technology are now also being utilised across different consumer industries. In case of e-retail, four major significant benefits of AI applications exist namely: personalisation, predictive analytics, chatbots, and marketing automation (Rai, 2020; Thomaz et al., 2020).Personalisation is a significant factor influencing adoption of AI (Kumar et al. 2019; Paschen et al., 2019). AI, based on customer data, involve wide application such as, automated personalized advertisement copy generation (Bang &Wojdynski, 2016;Deng et al., 2019); recommender systems for customers (Zanker et al., 2019); predicting and improving customer satisfaction through tailored marketing approach (Syam& Sharma, 2018; Daqar&Smoudy, 2019). These applications of AI positively improvecustomer behavior in different context. For instance, it improves purchase, loyalty, interactive marketing, value co-creation, brand usage, repurchase intention (Ifekanandu et al. 2023); in m-banking context it improves loyalty and repurchase intention (Bakhshandeh et al. 2023); improves loyalty in both shopping mall and e-retail purchase (Ameen et al. 2022; Chandra et al., 2022;Guttmann, 2021; Zeng et al. 2021); provide better customer experience in the case of social media marketing (Tran et al., 2020; Hayes et al., 2021); improves loyalty in case of fashion retailing industry (Jain et al., 2021). In generalized context, it improves overall customer journey (Smink et al., 2020; Gao and Liu 2022; Abrokwah-Larbi 2023).However, these personalization by AI utilize customer data often without full transparency (Peltier et al., 2023; Chen et al., 2022; Scarpi et al., 2022; Jain et al., 2021; Smink et al., 2020; Tran et al., 2020). People started to believe that there is an increased chance of potential loss associated with sharing of data and it forms a feeling of intrusion and privacy violation among customers (Chen et al., 2019; Kim et al., 2019; Zhu et al., 2017). It is termed as privacy risk of users and customers have started to become more intrusive towards these technologies (Smink et al., 2020). As a consequence, AI is not appreciated by all stakeholders (Mazurek and Malagocka, 2019; Pomfret et al., 2020). Customer privacy and security is under extensive analysis (Martin and Murphy, 2019; Vilmakumar et al., 2021), and it is becoming one of the critical concern for customers (Brill et al., 2019;Kietzmann et al., 2018; Mazurek and Malagocka, 2019). Privacy concern plays a critical role in negatively influencing customer behavior. Scholars (Pentina et al. 2016; Bandara et al., 2017) have pointed a negative influence of perceived data sharing risk and user behavior. Consistent with this finding many other scholars have also pointed a negative influence in different contexts. For instance, in the context of mobile payment (Kokolakis, 2017;Wottrich et al. 2018); online open market (Kim 2020); online shopping (Tham et al. 2019); contact tracing app (Hinch et al. 2020); social networking sites (Alemany et al. 2021). Found a negative influence in retail context (Cheah et al. 2022), it damages trust of customer (Plangger and Montecchi 2020), and companies must improve privacy policy mechanism (bandara et al. 2021).Interestingly, they have also showed that people still share their information because of its related perceived benefit. This dilemma between concern about sharing of data and its related benefit is termed asPrivacy Calculus Theory (PCT)' (Tham et al. 2019; Kim 2020).With two-dimension, perceived privacy concern and perceived benefit PCTprovides a significant theoretical basis for studying and describing the dilemma where customer appreciate and accept the value of data sharing while being aware of the fact of probable data exploitation (Dinev and Hart, 2006; Aguirre et al., 2015; Bleier and Eisenbeiss, 2015; Wang et al., 2016; Cloarec, 2020). PCT framework has been used to study customer behavior in various contexts, such as, new technologies' usage, personalized travel websites, retailing, hotels, social acceptance of automated technologies, influence of AI on disclosing information, in health care automation (Aguirre et al., 2016; Anic et al., 2019; Dinev and Hart, 2006; Lee and Cranage 2011; Xu et al., 2011; Zhu et al., 2017; Lephale 2021;Khaksar et al., 2024; Kronemann et al. 2023; singh et al. 2024).

The discussions have shed light on the following gaps-

Two important gaps have been observed from past literature; first, very few studies have considered taking AI-fashion retailing context under consideration for studying the influence of privacy risk and perceived benefit. Second, the influence ofpersonalization is unknown. It is understood that it influences the adoption of AI and it is a benefit derived from sharing of personal data. However, very few studies have considered a theory driven investigation for studying the influence of personalization as a mediator between privacy concern, perceived benefit and repurchase intention of customers in the AI-fashion retailing context. The present study tried to close this gap by applying PCT framework. The study examines the following research questions-

1. What role does privacy concern and perceived benefit plays on customerrepurchase intention in the context of AI-fashion retailing?
2. What role does personalization plays between privacy concern, perceived benefit and customer repurchase intention?

The study tries to answer this question based on the following objective-

1. To examine the influence of privacy concern and perceived benefit on customerrepurchase intention
2. To examine the influence of personalization as a mediator betweenprivacy concern, perceived benefit and customer repurchase intention

Literature Review-

AI fashion retail and repurchase intention-

AI has a substantial effect on RPI across different sectors. Research indicates that AI technologies improve customer experiences, which result in higher satisfaction and a greater likelihood of repeat purchases (Lei et al., 2023; Malhotra and Ramalingam, 2020). In particular, AI-driven approaches, including personalized recommendations, chatbots, and AI-enhanced sales processes, positively influence consumer purchasing behavior and brand loyalty, ultimately affecting RPI (Jangra and Jangra, 2022; Dwi Santy and Iffan, 2023). Furthermore, the quality of experiences provided by AI services is essential in determining customers' overall satisfaction and their willingness to repurchase using these services in the future. In summary, AI plays a crucial role in e-commerce by shaping RPI through improved shopping experiences and enhanced consumer behavior (Qin et al., 2022; Chen et al., 2023). AI notably impacts customer repurchase behavior by boosting satisfaction, trust, perceived value, and the overall experience (Jangra and Jangra, 2022). Therefore, it is reasonable to assume that AI will similarly influence customer repurchase intentions.

PCT and recent studies on it-

As per this theoretical framework consumer undertakes a cost and benefit analysis before making any decision. More specifically, customer judge their decision based on a trade-off between the cost of disclosing their personal information and benefits aligned with it (Culnan and Armstrong, 1999; Dinev and Hart, 2006; Xu et al., 2011). It is also assumed that various perceived benefits like, personalization, usefulness and social benefit etc. will reduce the negative influence of perceived risk and they will be more inclined towards sharing their personal information (Wang et al., 2016; Dine and Hart 2006.) In order to study customer behavior more accurately, different scholars have utilized PCT in different context such as, smart phone based health tracking applications (Fernandes and costa 2023),mobile applications (Jahari et al., 2022), social media or social networking sites (Guo et al. 2020; Hayes et al., 2021), and other digital technologies (Scarpi et al., 2022), Mobile location based services (Gutierrez et al. 2019), e-commerce (Zhu et al., 2017), social commerce (Sharma and Clossler, 2014), and mobile applications (Xu et al., 2011), focusing on the final decision of whether to disclosure information.

Development of Hypothesis-

Privacy concern-

Privacy concerns are negative attitude towards any type of data based technologies and it clusters around personal data collection and errors, unauthorized access and secondary use of it and this results into a more conservative behavior among customers (Baek& Morimoto, 2012; Lowry et al., 2012; Shin & Lin, 2016; Brinson et al., 2018; Gironda&Korgaonkar, 2018; Redondo & Aznar, 2018; Strycharz et al., 2019; Aksoy et al., 2021; Dinev et al., 2016). Various studies have disclosed, especially in the digital context, a negative relation between privacy concern and customers attitude towards sharing of information, usage behavior, participation inpurchase, repurchase, continued use intention and other different brand related behavior (Acquisti et al., 2015; Lee &Rha, 2016; Baruh and Popescu, 2017; Martin and Murphy, 2019; Oghazi et al., 2020; Wiese et al., 2020; Jahari et al., 2022). These suppress the potential of digitalization (Buchanan et al. 2007; Angst and Agarwal 2009; MüllerSeitz et al., 2009; Kumar et al., 2016; Baruh and Popescu, 2017; Mani and Chouk, 2017; Gutierrez et al., 2019; Vilmakumar et al., 2021). Consequently, it is proposed that:

Ha1: Privacy concern has a negative influence on repurchase intention of customers towards AI-fashion retailing context.

Ha2: Privacy concern negatively influence customers belief in personalization benefit providedby AI-fashion retailing applications.

Perceived Benefit-

Many studies have defined perceived benefit as a tendency of customers to completely assess the received benefit from information disclosure (Morosan and DeFranco, 2015; Xu et al., 2011; Zeng et al., 2020). It has a significant positive influence on customer behavior. For instance, some benefits, such as efficiency in multi-tasking, saving of time and cost, will reduce the negative influence of disclosing personal information (Jiang et al. 2022; Adapa et al., 2020;Loh, 2019; Poort et al., 2019; Morosan and DeFranco, 2015; Zhao et al. 2012; Xu et al., 2011). Scholars have concluded a positive influence of this factor on customer behavior in the context of m-Health applications (Fernandes and Costa 2023; Dinev et al., 2016); wearable devices *(Guo et al., 2013; Li, et al., 2016; Li et al., 2014);* food services mobile applications (Kang and Namkung , 2019).Further, scholars Vilmakumar et al., (2021) have concluded that if people perceive technology to be useful, they will ignore privacy related issues.Thus, we proposed the following hypotheses:

Ha3: Perceived benefits positively influence repurchase intention of customers towards AI-fashion retailing context.

Ha4: Perceived benefits positively influence customers belief in personalization benefit provided by AI-fashion retailing applications.

Personalisation-

This efficient marketing tactic helps various companies to approach customers uniquely and provide different advantages such as efficiency, convenience, individualization, and hospitality by saving time, effort and money (Chellappa& Sin, 2005; Ho and Tam 2005; Sheng et al., 2008; Montgomery & Smith, 2009; Tran, 2017; Aksoy et al., 2021). This helps to improve familiarity of content, accessibility, convenience, economic benefits, social advantages, customer well-being,decision making, and it suppress perceptions of privacy risk and improves the feelings of perceived benefit thereby developing a positive customer attitude (Banerjee & Dholakia 2008; Xu et al. 2009; Xu et al., 2011; Baek& Morimoto, 2012; Kim and Han, 2014; Gazley, et al. 2015; Park & Goering, 2016; Shin & Lin, 2016; Barth & Jong, 2017; Brinson et al., 2018; Gironda&Korgaonkar, 2018; Redondo & Aznar, 2018; Gutierrez et al. 2019; Kim et al., 2019; Strycharz et al., 2019). Similarly, we propose that:

Ha5: Personalisation will positively mediate the relationship between privacy concern, perceived benefit and repurchase intention of customers towards AI-fashion retailing context.

Methods and Materials-

Operationalization of constructs-

The constructs of this research were the privacy concerns, the perceived benefits, the personalization and the continued use of an AI-backed shopping application. These constructs were operationalized based on previous studies, working of AI, and current literature. Although these indicators have been used in studies related to other contexts, the pilot test (table: 3) of this study confirmed that they are relevant to the AI-marketing context. The operationalized terms are shown in Table 1.

Table 1: Showing operationalization of constructs

SL. NO.	Construct	Meaning based on existing concept	Operationalized meaning
1	Privacy Concern	It is the extent to which a user or person believes that there is a possibility of negative consequence related with information sharing.	It is the extent to which a user or person, due to privacy policy disclosure, believes that there is a negative consequence with sharing of information for AI-fashion retail applications.
2	Perceived Benefit	It is the extent to which users or customers believe that they will receive different kinds of benefit on information sharing	It is the extent to which a user belief that, by sharing information with AI-fashion retail applications, they will receive different types of benefits.
3	Repurchase intention	It is the tendency of customers to purchase again from the shopping platform	It is the intention of users or consumers to repurchase AI-fashion retailing applicationbecause of its benefit and reduced privacy concern due to privacy policy disclosures.
4	Personalization	It is a designed skill of a system to recognize and treat its consumers as distinct individuals by communicating tailor made contents.	It is the extent by which users or consumers, based on shared data, receive personalised marketing contents and experience reduced privacy concern and improved perceived benefit.

Source: Computed by researchers

Sample Design-

This study did not utilize any specific quantitative formula for selecting sample size rather different assumptions of various scholars was checked. Scholar (Boomsma, 1985) has suggested sample size of 100 or 200 would be appropriate, whereas, scholars (Bentler& Chou, 1987; Bollen, 1989) have stated that every study must keep 5 or 10 observations or respondents per variable and Nunnally (1994) has discussed to keep 10 cases per estimated parameter (Nunnally, 1994) as different thumb rules. This study collected a total of 252responses. The chosen respondents were current users of AI fashion retail applications based in the eastern region of West Bengal, India. Data collection was conducted through stratified random sampling. The population was categorized into three groups according to demographic factors: experience with application usage, income level, and education. Once the strata were established, participants were selected randomly for the data collection process. Data was collected with the help of Google forms.

Measurement instrument-

The first part of questionnaire was developed for collecting demographic information only. This section includes only Age, Gender, Income, Education, usage experience. Second part of the questionnaire was designed for collecting responses about model variables. These model variables was measured with the help of a 5-point likert scale (1 being strongly disagree and 5 being strongly agree). Initially, during pilot study, this part had 25 items for testing 4 test variables *(see table: 2)*. the revised questionnaire, based on pilot survey and its suitability, had only 24 items.

Table 2: Measures

Test Variables	Number of Items	Source(s)
Privacy Concern	5	(Lee and Cranage, 2011; Xu et al., 2011; Malhotra et al., 2004)
Perceived Benefit	5	(Unni and Harmon 2007; Sun et al. 2015; Hsu and Lin 2016)
Personalisation	5	(Baek and Morimoto 2012; Xu et al. 2011;

		Kim and Han 2014)
Repurchase Intention	9	(Bhattacherjee, 2001; Han and Yang, 2018)

Source: Computed by researchers

Collected data was analysed by utilizing Structural Equation Modeling (SEM). SEM is divided into two parts; first part is concerned about validating the measurement model known as Confirmatory Factor Analysis (CFA) and second part is concerned for testing the extent and direction of the test variables.

Results and Discussion-

At first, a pilot survey was conducted for ensuring reliability of the data collection instrument. The value denotes that the scale is a reliable scale (Hair et al., 2017) (*see table: 3)*

Table 3: Reliability Statistics

Cronbach's Alpha	N of Items
0.894	24

Source: Primary Data

The Demographic profile of respondents: Data analysis showed that out of 252 respondents 56% of respondents were female and 44% respondents were male. Only 23.4% of respondents were from the higher income group of people i.e. 70000 and above, majority of the respondents, 42.9% of respondents, were belonged from the above average income group i.e. monthly income of 50000-70000, 27.4% of the respondents were from average income group of people i.e. 30000-50000, and only 5.6% of the respondents were from the lower income group of people. Out of 252 respondents only 17.9% were within the age group of 23-28, 36.9% of people were within the age group of 29.34% and majority of respondents i.e. 45.2% within the range of 35-40.

In order to ensure and identify the items contributing to each existing construct, even in AI-fashion retailing context, an Exploratory Factor Analysis (EFA) was carried out. EFA was utilized using Principal Component Analysis (PCA) with Varimax rotation. As (table: 4-6) showing that the collected data were effective and acceptable for further factor exploration (Pallant, 2020). This analysis extracted 4 factors (*table: 6)*. These 4 factors were explaining 63.984 percent of total variance. During the EFA, based on the recommendations by Hair et al. (2014), factor loadings below .50 were suppressed. Indicators v21-v25 were loaded in first component i.e. *PC*. Indicators v6-v10 was loaded in *PB* whereas, indicators v1-v5 and v16-v19 were loaded in the *RPI* and lastly the indicators v12-v15 was loaded in *PER*. The extracted components were further explored using CFA using AMOS 20.

Table 4: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.841
Bartlett's Test of Sphericity	Approx. Chi-Square	4599.945
	Df	300
	Sig.	0.000

Source: Primary Data

Table 5: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.415	33.662	33.662	8.415	33.662	33.662	4.758	19.030	19.030
2	3.844	15.378	49.039	3.844	15.378	49.039	4.268	17.073	36.103
3	2.144	8.577	57.616	2.144	8.577	57.616	3.819	15.276	51.379
4	1.592	6.368	63.984	1.592	6.368	63.984	3.151	12.605	63.984

Source: Primary Data

Table 6: Rotated Component Matrix[a]

	Component

	1	2	3	4
v1	0.720			
v2	0.731			
v3	0.791			
v4	0.672			
v5	0.524	0.506		
v6		0.690		
v7		0.782		
v8		0.823		
v9		0.803		
v10		0.725		
v11				0.641
v12				0.819
v13				0.830
v14				0.744
v15				0.609
v16	0.532			
v17	0.572			
v18	0.602			
v19	0.667			
v20				
v21			0.838	
v22			0.834	
v23			0.903	
v24			0.902	
v25			0.869	
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.				
a. Rotation converged in 5 iterations.				

Source: Primary Data

Following the confirmation of loadings with their respective factors, the indicators were appropriately renamed. V1 to V5 and V16 to V19 were designated as RPI1 to RPI5 and RIP6 to RPI9, signifying the factor of Repurchase Intention (RPI). Likewise, V6 to V10 were changed to PBs1 to PBs5, representing the construct of Perceived Benefits (PBs). The indicators V11 to V15 were updated to PCs1 to PCs5, indicating the factor of Privacy Concerns (PCs). Finally, V21 to V25 were renamed as PER1 to PER5, reflecting the factors related to Personalized Recommendations (PER). The CFA model was analysed by loading all the items to their respective factors as obtained from EFA.Checking model fit, Convergent validity and discriminant validity is pre-requisite for developing a Structural Equation Modelling (SEM). At first, the model exhibited low values in the fit measures, and its chi-square (χ^2)/df ratio was elevated. Following an assessment of the modification indices produced by SPSS AMOS, the items with the most insignificant impact on the model were eliminated. This adjustment suggests a decrease in the chi-square (χ^2), thereby enhancing its validity (MacCallum, 1981; Satorra, 1989; Sörbom, 1989; MacCallum et al., 1992; Bollen, 2014). As (table: 7) showing that all the required fit indices were falling within the suggested acceptable threshold (Hair et al. 1998). Further, for achieving both the above-mentioned validities, Composite Reliability (CR), Average Variance Extracted (AVE) and square root of AVE was utilized (Table 8). As suggested by (Hair et al., 2006; Fornell&Larcker, 1981) statistical Values of both the test are significant. Therefore, all the assumptions were met for moving further with SEM.

Table 7: Model fit measures

Model Fit indices	**GFI**	**CFI**	**SRMR**	**Pclose**	**RMSEA**	**CMIN/DF**

Values	0.930	0.969	0.056	0.161	0.058	1.857

Source: *Primary Data (using Gaskin and Lim 2006 Statistical tool package add-on for SPSS AMOS)*

Table 8: Calculation of Discriminate and Convergent Validity

	CR	AVE	MSV	MaxR(H)	PERs	PCs	PBs	RPI
PERs	0.833	0.567	0.267	0.920	**0.753**			
PCs	0.913	0.681	0.016	0.938	0.009	**0.825**		
PBs	0.867	0.686	0.202	0.896	0.396	-0.128	**0.828**	
RPI	0.845	0.649	0.267	0.903	0.517	0.043	0.449	**0.806**

Source: *Primary Data (using Gaskin and Lim 2006 Statistical tool package add-on for SPSS AMOS)*

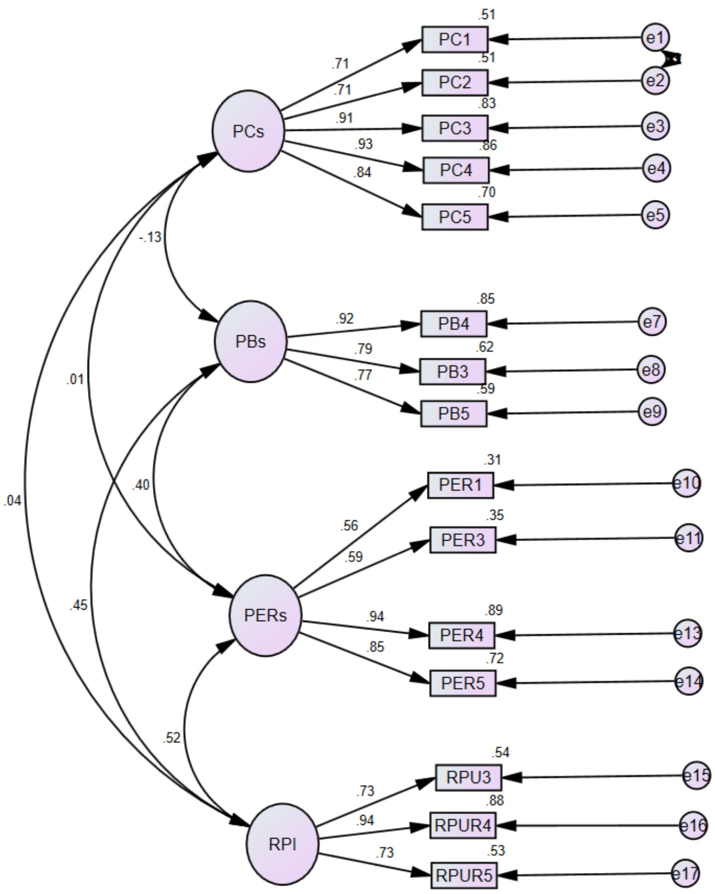

Figure 3: Graphical representation of model fit

Source: SPSS AMOS output based on primary data

Testing of the hypothesis-

The regression analysis presented in Table 9 illustrates the outcomes of the hypotheses tests conducted on this empirically validated model. The data indicates that PCs does not have a significant effect on customers' repurchase intentions nor on their beliefs regarding personalization. Consequently, hypotheses Ha1 (Stand. β=0.064, p>0.05) and Ha2 (Stand. β=0.059, p>0.05) are rejected. In contrast, PB demonstrates a significant influence on RPI (Stand. β=0.222, p<0.05) and PER (Stand. β=0.437, p<0.05), resulting in the acceptance of Ha3 and Ha4. Additionally, Table 9 reveals that PER significantly mediates the relationship, enhancing it (Stand. β=0.514, p<0.05), which supports the acceptance of Ha5.

Table 9: Regression estimates and testing of hypotheses

			Estimate	Stand. B	S.E.	C.R.	P	Decision
PER	<---	PB	0.292	0.437	0.058	5.048	-	Ha4 accepted

PER	<---	PC	0.037	0.059	0.041	0.915	0.36	Ha2 rejected
RPUR	<---	PB	0.237	0.222	0.075	3.169	0.002	Ha3 accepted
RPUR	<---	PER	0.823	0.514	0.148	5.572	-	Ha5accepted
RPUR	<---	PC	0.066	0.064	0.06	1.094	0.274	Ha$_1$ Rejected

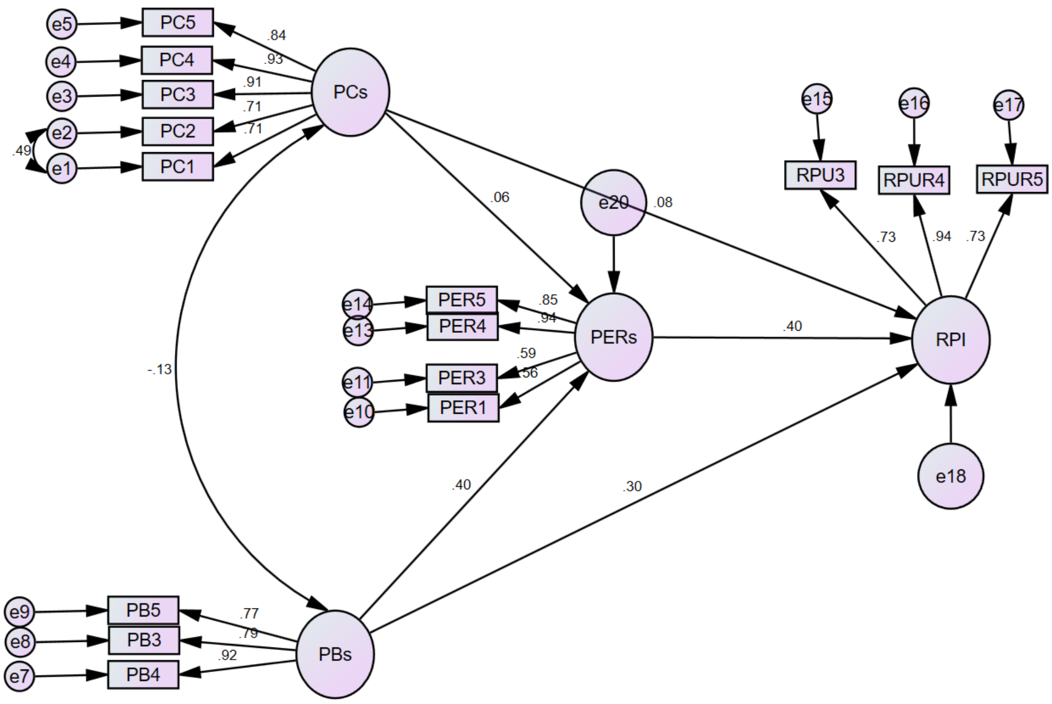

Figure 4: Graphical representation of path analysis.
Source: SPSS AMOS output based on primary data.

Discussion-

Objective 1- To examine the influence of privacy concern and perceived benefit on customer repurchase intention

Ha1 and Ha2, which proposed a negative influence between PCs, RPI and PER, found no support in the data analysis. The study measured privacy concernthrough third party access or loss of personal data. This finding is inconsistent with the studies (Kumar et al., 2016; Gutierrez et al., 2019; Thomaz et al. 2020) where scholars have discussed that the privacy concern of users or customers has a negative influence on customer behaviour. There may be two primary reasons for this inconsistent finding. First, it could stem from how PC was operationalized. Second, the presence of experienced respondents from the "Application Usage Experience" group might also contribute to this issue. In contrast to earlier studies, this research incorporated the suggestions of Bandara et al. (2017) in defining the construct. They indicated that PC arises from a lack of understanding regarding the consequences of data disclosure and that the impact of PC diminishes as consumers' knowledge grows. The participants in this study had experience with how AI fashion retail applications function. Additionally, prior research has shown that customers' understanding of product features, novelty, and unique differentiation positively influences their behavior (Tanner and Wölfing Kast, 2003; Petina et al., 2016). These earlier findings support the conclusion that PC has an insignificant effect on RPI and PER.

Ha3 and Ha4, which assumed a positive influence between PB, PER and RPI, found support from data analysis. The analysis suggests that customers are highly motivated to purchase because of data sharing benefits. The result agrees with previous studies as well. Numerous studies have demonstrated the substantial influence of PB on consumer behavior (Keith et al., 2010; Xu et al., 2011; Wang et al., 2016; Shanahan et al., 2019; Fernandes and Pereira, 2021; Vimalkumar et al., 2021; McKee et al., 2023). These consistent results highlight the relevance of PB in a range of technology-driven settings.

Objective 2- To examine the influence of personalization as a mediator between privacy concern, perceived benefit and customer repurchase intention.

Ha5, proposing a positive mediating influence of personalization between privacy concern, perceived benefit, and repurchase intention found support in data analysis. This finding is in line with past literatures on personalization as a separate benefit and found its positive influence(Kallier 2017; Guo and Jiang 2023).The positive association implies that company offerings which completely resonate with a customer's personality improves customer behavior and reduces the negative influence. Various studies have revealed the beneficial impact of PER. For example, research has shown its positive effects on customer repurchase intentions, brand engagement, overall loyalty, and customer experience (Bakhshandeh et al., 2023; Tran et al., 2022; Ameen et al., 2021; Rabby, 2021; Pearson, 2019).

Conclusion-

This study made an attempt to augment the ongoing research on customer behavior in the context of AI-fashion retailing. In conclusion, there were two objectives of this study, first was to identify the influence of privacy concern and perceived benefit on the re-use intentionin the context of AI-fashion retailing. The second objective was to check whether personalized offering improves the relationship. This study has revealed two important relationships. First, it showed that privacy concern does not have any negative influence on the purchase intention. Second, it is confirmed that personalization, a benefit of data sharing, is an important mediating factor. This factor plays a crucial role of partial mediator that reduces the negative impact and influence of privacy concern, positively influence the perceived benefit and the purchase intention. This mediating relationship in the proposed empirical model must be considered to be important for shaping the future study on AI-marketing literature.

Implications-

This study has certain practical and theoretical implications. From the theoretical perspective, this study has extended the current literature on AI-fashion retailing. More specifically, this study has provided an empirically tested model in which personalization was used as a mediator and extends the current literature in the domain of AI-fashion retailing and customers' perception related to privacy concern and perceived benefit. Further, this is among the first study in the context of AI fashion retailing that hashas showed a significant relationship between privacy concern, perceived benefit, and personalisation. From the practical point of view, marketers must focus on improving the awareness about personalization. The awareness must be spread by using marketing communication techniques and informing customers about how their data is being utilized by these applications to improve personalized offerings, such as curated style suggestions and discounts based on browsing patterns, etc. Moreover, fashion retail managers must focus on utilizing non-sensitive data and providing an easy opt-in option for customization. This will enable customers to keep or remove their personal data from the application whenever necessary. This will give customers a feeling that they are in control of their privacy, which may improve the positive association with other variables. At present, retailers need to focus on positioning personalized benefits as a significant integral part of the customer journey. This will help deepen customer engagement and loyalty. Additionally, retailers must be very clear about their data protection policies without overemphasizing them or turning them into a marketing effort, which might raise unnecessary concerns among customers. There must be a balance point where privacy policies are easily accessible in a concise manner, without making them the focal point. This can be helpful in improving customer trust without having a deterring effect on personalization benefits and perceived value. Marketers must communicate these things with the target market about their data safety, privacy policy and various personalized benefits they can get.

Limitation and future direction-

Most of the respondents were approached informally using different types of digital platforms. This is one of the most critical constraints that might have influenced the outcome of this study. Another limitation was respondents were selected from a specific part of West-Bengal. Future studies can be extended to other parts of the country. Further, they were mostly young. A study with diversified sample characteristics involves respondents from higher, middle and lower age groups may conclude with a different perspective related to this research problem. Lack of empirical literature on personalization as a mediator, in the context of AI marketing, has also restricted further validation and discussion of the findings. Also, this study was completely focused on AI-shopping applications and users' perception related to data sharing. AI is an emerging technology and future studies can be made on other areas of marketing, other than online shopping and consumer behaviour. Again, disclosure of privacy policy must be utilised as a separate dimension in future studies and it must be checked whether it can change the negative influence of privacy concern to positive on customer attitude. Lastly, the emerged relationship between the variables, as discussed in testing of hypotheses section, must be considered in future studies.

Reference-

Abrokwah-Larbi, K. (2023). The role of generative artificial intelligence (GAI) in customer personalization (CP) development in SMEs: A theoretical framework and research propositions. *Industrial Artificial Intelligence, 1*(1), 11.

Acquisti, A., Brandimarte, L., & Loewenstein, G. (2015). Privacy and human behavior in the age of information. *Science, 347*(6221), 509-514. https://doi.org/10.1126/science.aaa1465

Adapa, S., Fazal-e-Hasan, S. M., Makam, S. B., Azeem, M. M., & Mortimer, G. (2020). Examining the antecedents and consequences of perceived shopping value through smart retail technology. *Journal of Retailing and Consumer Services, 52,* 101901. https://doi.org/10.1016/j.jretconser.2019.101901

Aguirre, E., Roggeveen, A. L., Grewal, D., & Wetzels, M. (2016). The personalization-privacy paradox: Implications for new media. *Journal of Consumer Marketing, 33*(2), 98-110. https://doi.org/10.1108/JCM-06-2015-1458

Albert, T. C., Goes, P. B., & Gupta, A. (2004). GIST: A model for design and management of content and interactivity of customer-centric web sites. *MIS Quarterly,* 161-182. https://doi.org/10.2307/25148633

Alemany, J., Del Val, E., & Garcia-Fornes, A. M. (2021). "Who should I grant access to my post?": Identifying the most suitable privacy decisions on online social networks. *Internet Research, 31*(4), 1290-1317. https://doi.org/10.1108/INTR-12-2019-0517

Ameen, N., Hosany, S., & Paul, J. (2022). The personalization-privacy paradox: Consumer interaction with smart technologies and shopping mall loyalty. *Computers in Human Behavior, 126,* 106976. https://doi.org/10.1016/j.chb.2021.106976

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior, 114,* 106548. https://doi.org/10.1016/j.chb.2020.106548

Angst, C. M., & Agarwal, R. (2009). Adoption of electronic health records in the presence of privacy concerns: The elaboration likelihood model and individual persuasion. *MIS Quarterly,* 339-370. https://doi.org/10.2307/20650295

Anić, I. D., Škare, V., & Milaković, I. K. (2019). The determinants and effects of online privacy concerns in the context of e-commerce. *Electronic Commerce Research and Applications, 36,* 100868. https://doi.org/10.1016/j.elerap.2019.100868

Baek, T. H., & Morimoto, M. (2012). Stay away from me. *Journal of Advertising, 41*(1), 59-76.

Baek, T. H., & Morimoto, M. (2012). Stay away from me. *Journal of Advertising, 41*(1), 59-76.

Bakhshandeh, G., Sharifi, S., & Rezaei, S. M. (2023). Influence of personalisation and hedonic motivation on repurchase intention: The mediating role of customer experience and loyalty. *International Journal of Services, Economics and Management, 14*(1), 42-57.

Bakhshandeh, G., Sharifi, S., & Rezaei, S. M. (2023). Influence of personalisation and hedonic motivation on repurchase intention: The mediating role of customer experience and loyalty. *International Journal of Services Economics and Management, 14*(1), 42.

Bandara, R., Fernando, M., & Akter, S. (2017). The privacy paradox in the data-driven marketplace: The role of knowledge deficiency and psychological distance. *Procedia Computer Science, 121,* 562-567.

Bandara, R., Fernando, M., & Akter, S. (2021). Managing consumer privacy concerns and defensive behaviours in the digital marketplace. *European Journal of Marketing, 55*(1), 219-246.

Banerjee, S. S., & Dholakia, R. R. (2008). Mobile advertising: Does location-based advertising work? *International Journal of Mobile Marketing.*

Bang, H., & Wojdynski, B. W. (2016). Tracking users' visual attention and responses to personalized advertising based on task cognitive demand. *Computers in Human Behavior, 55,* 867-876.

Barth, S., & De Jong, M. D. (2017). The privacy paradox – Investigating discrepancies between expressed privacy concerns and actual online behavior – A systematic literature review. *Telematics and Informatics, 34*(7), 1038-1058.

Baruh, L., & Popescu, M. (2017). Big data analytics and the limits of privacy self-management. *New Media & Society, 19*(4), 579-596.

Bentler, P. M., & Chou, C. P. (1987). Practical issues in structural modeling. *Sociological Methods & Research, 16*(1), 78-117.

Bhattacherjee, A. (2001). An empirical analysis of the antecedents of electronic commerce service continuance. *Decision Support Systems, 32*(2), 201-214.

Bollen, K. A. (2014). *Structural equations with latent variables.* John Wiley & Sons.

Bollen, K. A. (1989). *Structural equations with latent variables* (Vol. 210). John Wiley & Sons.

Boomsma, A. (1985). Nonconvergence, improper solutions, and starting values in LISREL maximum likelihood estimation. *Psychometrika, 50,* 229-242.

Brinson, N. H., Eastin, M. S., & Cicchirillo, V. J. (2018). Reactance to personalization: Understanding the drivers behind the growth of ad blocking. *Journal of Interactive Advertising, 18*(2), 136-147.

Buchanan, T., Paine, C., Joinson, A. N., & Reips, U. D. (2007). Development of measures of online privacy concern and protection for use on the Internet. *Journal of the American Society for Information Science and Technology, 58*(2), 157-165.
Cavdar Aksoy, N., Tumer Kabadayi, E., Yilmaz, C., & Kocak Alan, A. (2021). A typology of personalisation practices in marketing in the digital age. *Journal of Marketing Management, 37*(11-12), 1091-1122.
Chandra, S., Verma, S., Lim, W. M., Kumar, S., & Donthu, N. (2022). Personalization in personalized marketing: Trends and ways forward. *Psychology & Marketing, 39*(8), 1529-1562.
Cheah, J. H., Lim, X. J., Ting, H., Liu, Y., & Quach, S. (2022). Are privacy concerns still relevant? Revisiting consumer behaviour in omnichannel retailing. *Journal of Retailing and Consumer Services, 65,* 102242.
Chellappa, R. K., & Sin, R. G. (2005). Personalization versus privacy: An empirical examination of the online consumer's dilemma. *Information Technology and Management, 6,* 181-202.
Chen, Q., Feng, Y., Liu, L., & Tian, X. (2019). Understanding consumers' reactance of online personalized advertising: A new scheme of rational choice from a perspective of negative effects. *International Journal of Information Management, 44,* 53-64.
Chen, S., Li, X., Liu, K., & Wang, X. (2023). Chatbot or human? The impact of online customer service on consumers' purchase intentions. *Psychology & Marketing, 40*(11), 2186-2200.
Chen, X., Sun, J., & Liu, H. (2022). Balancing web personalization and consumer privacy concerns: Mechanisms of consumer trust and reactance. *Journal of Consumer Behaviour, 21*(3), 572-582.
Daqar, M. A. A., & Smoudy, A. K. (2019). The role of artificial intelligence on enhancing customer experience. *International Review of Management and Marketing, 9*(4), 22.
Deng, S., Tan, C. W., Wang, W., & Pan, Y. (2019). Smart generation system of personalized advertising copy and its application to advertising practice and research. *Journal of Advertising, 48*(4), 356-365.
Dinev, T., Albano, V., Xu, H., D'Atri, A., & Hart, P. (2016). Individuals' attitudes towards electronic health records: A privacy calculus perspective. *Advances in Healthcare Informatics and Analytics,* 19-50.
Dwi Santy, R., & Iffan, M. (2023). The effect of artificial intelligence and gamification on online purchase intention mediated by customer experience: Study on Indonesian marketplace users. *Mix: Jurnal Ilmiah Manajemen, 13*(1).
Fernandes, T., & Costa, M. (2023). Privacy concerns with COVID-19 tracking apps: A privacy calculus approach. *Journal of Consumer Marketing, 40*(2), 181-192.
Fernandes, T., & Pereira, N. (2021). Revisiting the privacy calculus: Why are consumers (really) willing to disclose personal data online? *Telematics and Informatics, 65,* 101717.
Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.
Fox, G. (2020). "To protect my health or to protect my health privacy?" A mixed-methods investigation of the privacy paradox. *Journal of the Association for Information Science and Technology, 71*(9), 1015-1029.
Gao, Y., & Liu, H. (2022). Artificial intelligence-enabled personalization in interactive marketing: A customer journey perspective. *Journal of Research in Interactive Marketing.* Advance online publication, 1-18.
Gazley, A., Hunt, A., & McLaren, L. (2015). The effects of location-based-services on consumer purchase intention at point of purchase. *European Journal of Marketing, 49*(9/10), 1686-1708.
Gironda, J. T., & Korgaonkar, P. K. (2018). iSpy? Tailored versus invasive ads and consumers' perceptions of personalized advertising. *Electronic Commerce Research and Applications, 29,* 64-77.
Gironda, J. T., & Korgaonkar, P. K. (2018). iSpy? Tailored versus invasive ads and consumers' perceptions of personalized advertising. *Electronic Commerce Research and Applications, 29,* 64-77.
Guo, B., & Jiang, Z. B. (2023). Influence of personalised advertising copy on consumer engagement: A field experiment approach. *Electronic Commerce Research,* 1-30.
Guo, J., Li, N., Wu, Y., & Cui, T. (2020). Examining help requests on social networking sites: Integrating privacy perception and privacy calculus perspectives. *Electronic Commerce Research and Applications, 39,* 100828.
Guo, X., Sun, Y., Wang, N., Peng, Z., & Yan, Z. (2013). The dark side of elderly acceptance of preventive mobile health services in China. *Electronic Markets, 23,* 49-61.
Gutierrez, A., O'Leary, S., Rana, N. P., Dwivedi, Y. K., & Calle, T. (2019). Using privacy calculus theory to explore entrepreneurial directions in mobile location-based advertising: Identifying intrusiveness as the critical risk factor. *Computers in Human Behavior, 95,* 295-306.

Guttman, N., & Lev, E. (2021). Ethical issues in COVID-19 communication to mitigate the pandemic: Dilemmas and practical implications. *Health Communication, 36*(1), 116-123.
Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (6th ed.).
Han, S., & Yang, H. (2018). Understanding adoption of intelligent personal assistants: A parasocial relationship perspective. *Industrial Management & Data Systems, 118*(3), 618-636.
Hayes, J. L., Brinson, N. H., Bott, G. J., & Moeller, C. M. (2021). The influence of consumer–brand relationship on the personalized advertising privacy calculus in social media. *Journal of Interactive Marketing, 55*(1), 16-30.
Hinch, R., Probert, W., Nurtay, A., Kendall, M., Wymant, C., Hall, M., Lythgoe, K., Cruz, A. B., Zhao, L., Stewart, A., & Ferretti, L. (2020). Effective configurations of a digital contact tracing app: A report to NHSX. *Retrieved July 23, 2020.*
Ho, S. Y., & Tam, K. Y. (2005). An empirical examination of the effects of web personalization at different stages of decision making. *International Journal of Human-Computer Interaction, 19*(1), 95-112.
Hsu, C. L., & Lin, J. C. C. (2008). Acceptance of blog usage: The roles of technology acceptance, social influence, and knowledge sharing motivation. *Information & Management, 45*(1), 65-74.
Ifekanandu, C. C., Anene, J. N., Iloka, C. B., & Ewuzie, C. O. (2023). Influence of artificial intelligence (AI) on customer experience and loyalty: Mediating role of personalization. *Journal of Data Acquisition and Processing, 38*(3), 1936.
Jahari, S. A., Hass, A., Hass, D., & Joseph, M. (2022). Navigating privacy concerns through societal benefits: A case of digital contact tracing applications. *Journal of Consumer Behaviour, 21*(3), 625-638.
Jain, G., Paul, J., & Shrivastava, A. (2021). Hyper-personalization, co-creation, digital clienteling, and transformation. *Journal of Business Research, 124*, 12-23.
Jangra, G., & Jangra, M. (2022, September). Role of artificial intelligence in online shopping and its impact on consumer purchasing behaviour and decision. In *2022 Second International Conference on Computer Science, Engineering and Applications (ICCSEA)* (pp. 1-7). IEEE.
Jiang, X., Goh, T. T., & Liu, M. (2022). On students' willingness to use online learning: A privacy calculus theory approach. *Frontiers in Psychology, 13*, 880261.
Kallier, S. M. (2017). The influence of real-time marketing campaigns of retailers on consumer purchase behavior. *International Review of Management and Marketing, 7*(3), 126-133.
Kang, J. W., & Namkung, Y. (2019). The role of personalization on continuance intention in food service mobile apps: A privacy calculus perspective. *International Journal of Contemporary Hospitality Management, 31*(2), 734-752.
Keith, M. J., Babb, J. S., Furner, C. P., & Abdullat, A. (2010). Privacy assurance and network effects in the adoption of location-based services: An iPhone experiment.
Khaksar, S. M. S., Shahmehr, F. S., Miah, S., Daim, T., & Ozdemir, D. (2024). Privacy concerns versus personalization benefits in social robot acceptance by employees: A paradox theory—Contingency perspective. *Technological Forecasting and Social Change, 198*, 123034.
Kietzmann, J., Paschen, J., & Treen, E. (2018). Artificial intelligence in advertising: How marketers can leverage artificial intelligence along the consumer journey. *Journal of Advertising Research, 58*(3), 263-267.
Kim, D., Park, K., Park, Y., & Ahn, J. H. (2019). Willingness to provide personal information: Perspective of privacy calculus in IoT services. *Computers in Human Behavior, 92*, 273-281.
Kim, S. S. (2020). Purchase intention in the online open market: Do concerns for e-commerce really matter? *Sustainability, 12*(3), 773.
Kim, Y. J., & Han, J. (2014). Why smartphone advertising attracts customers: A model of web advertising, flow, and personalization. *Computers in Human Behavior, 33*, 256-269.
Kokolakis, S. (2017). Privacy attitudes and privacy behaviour: A review of current research on the privacy paradox phenomenon. *Computers & Security, 64*, 122-134.
Kronemann, B., Kizgin, H., Rana, N., & Dwivedi, Y. K. (2023). How AI encourages consumers to share their secrets? The role of anthropomorphism, personalization, and privacy concerns and avenues for future research. *Spanish Journal of Marketing-ESIC, 27*(1), 3-19.
Kumar, V., Dixit, A., Javalgi, R. G., & Dass, M. (2016). Research framework, strategies, and applications of intelligent agent technologies (IATs) in marketing. *Journal of the Academy of Marketing Science, 44*, 24-45.
Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review, 61*(4), 135-155.
Lee, C. H., & Cranage, D. A. (2011). Personalization–privacy paradox: The effects of personalization and privacy assurance on customer responses to travel websites. *Tourism Management, 32*(5), 987-994.

Lee, H., Park, H., & Kim, J. (2013). Why do people share their context information on social network services? A qualitative study and an experimental study on users' behavior of balancing perceived benefit and risk. *International Journal of Human-Computer Studies, 71*(9), 862-877.
Lee, J. M., & Rha, J. Y. (2016). Personalization–privacy paradox and consumer conflict with the use of location-based mobile commerce. *Computers in Human Behavior, 63*, 453-462.
Lei, C., Hossain, M. S., & Wong, E. (2023). Determinants of repurchase intentions of hospitality services delivered by artificially intelligent (AI) service robots. *Sustainability, 15*(6), 4914.
Lephale, T. R. (2021). *Product personalisation in the era of big data: The influence on customer loyalty* (Doctoral dissertation, University of Pretoria).
Li, H., Wu, J., Gao, Y., & Shi, Y. (2016). Examining individuals' adoption of healthcare wearable devices: An empirical study from privacy calculus perspective. *International Journal of Medical Informatics, 88*, 8-17.
Li, T., & Slee, T. (2014). The effects of information privacy concerns on digitizing personal health records. *Journal of the Association for Information Science and Technology, 65*(8), 1541-1554.
Loh, E. K. (2019). What we know about expectancy-value theory, and how it helps to design a sustained motivating learning environment. *System, 86*, 102119.
MacCallum, R. (1986). Specification searches in covariance structure modeling. *Psychological Bulletin, 100*(1), 107.
MacCallum, R. C., Roznowski, M., & Necowitz, L. B. (1992). Model modifications in covariance structure analysis: The problem of capitalization on chance. *Psychological Bulletin, 111*(3), 490.
Malhotra, G., & Ramalingam, M. (2023). Perceived anthropomorphism and purchase intention using artificial intelligence technology: Examining the moderated effect of trust. *Journal of Enterprise Information Management*.
Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). Internet users' information privacy concerns (IUIPC): The construct, the scale, and a causal model. *Information Systems Research, 15*(4), 336-355.
Mani, Z., & Chouk, I. (2017). Drivers of consumers' resistance to smart products. *Journal of Marketing Management, 33*(1-2), 76-97.
Martin, K. D., & Murphy, P. E. (2017). The role of data privacy in marketing. *Journal of the Academy of Marketing Science, 45*, 135-155.
Mazurek, G., & Małagocka, K. (2019). Perception of privacy and data protection in the context of the development of artificial intelligence. *Journal of Management Analytics, 6*(4), 344-364.
McKee, K. M., Dahl, A. J., & Peltier, J. W. (2023). Gen Z's personalization paradoxes: A privacy calculus examination of digital personalization and brand behaviors. *Journal of Consumer Behaviour*.
Montgomery, A. L., & Smith, M. D. (2009). Prospects for personalization on the Internet. *Journal of Interactive Marketing, 23*(2), 130-137.
Morosan, C., & DeFranco, A. (2015). Disclosing personal information via hotel apps: A privacy calculus perspective. *International Journal of Hospitality Management, 47*, 120-130.
Müller-Seitz, G., Dautzenberg, K., Creusen, U., & Stromereder, C. (2009). Customer acceptance of RFID technology: Evidence from the German electronic retail sector. *Journal of Retailing and Consumer Services, 16*(1), 31-39.
Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory*. McGraw-Hill.
Oghazi, P., Schultheiss, R., Chirumalla, K., Kalmer, N. P., & Rad, F. F. (2020). User self-disclosure on social network sites: A cross-cultural study on Facebook's privacy concepts. *Journal of Business Research, 112*, 531-540.
Pallant, J. (2020). *SPSS survival manual: A step by step guide to data analysis using IBM SPSS*. Routledge.
Park, D. Y., & Goering, E. M. (2016). The health-related uses and gratifications of YouTube: Motive, cognitive involvement, online activity, and sense of empowerment. *Journal of Consumer Health on the Internet, 20*(1-2), 52-70.
Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *Journal of Business & Industrial Marketing, 34*(7), 1410-1419.
Pearson, A. (2019). Personalisation the artificial intelligence way. *Journal of Digital & Social Media Marketing, 7*(3), 245-269.
Peltier, J. W., Dahl, A. J., & Schibrowsky, J. A. (2023). Artificial intelligence in interactive marketing: A conceptual framework and research agenda. *Journal of Research in Interactive Marketing* (ahead-of-print).
Pentina, I., Zhang, L., Bata, H., & Chen, Y. (2016). Exploring privacy paradox in information-sensitive mobile app adoption: A cross-cultural comparison. *Computers in Human Behavior, 65*, 409-419.
Plangger, K., & Montecchi, M. (2020). Thinking beyond privacy calculus: Investigating reactions to customer surveillance. *Journal of Interactive Marketing, 50*(1), 32-44.

Pomfret, L., Previte, J., & Coote, L. (2020). Beyond concern: Socio-demographic and attitudinal influences on privacy and disclosure choices. *Journal of Marketing Management, 36*(5-6), 519-549.
Poort, I., Jansen, E., & Hofman, A. (2019). Intercultural group work in higher education: Costs and benefits from an expectancy-value theory perspective. *International Journal of Educational Research, 93*, 218-231.
Qin, M., Zhu, W., Zhao, S., & Zhao, Y. (2022). Is artificial intelligence better than manpower? The effects of different types of online customer services on customer purchase intentions. *Sustainability, 14*(7), 3974.
Rabby, F., Chimhundu, R., & Hassan, R. (2021). Artificial intelligence in digital marketing influences consumer behaviour: A review and theoretical foundation for future research. *Academy of Marketing Studies Journal, 25*(5), 1-7.
Rai, A. (2020). Explainable AI: From black box to glass box. *Journal of the Academy of Marketing Science, 48*, 137-141.
Redondo, I., & Aznar, G. (2018). To use or not to use ad blockers? The roles of knowledge of ad blockers and attitude toward online advertising. *Telematics and Informatics, 35*(6), 1607-1616.
Robins, F. (2003). The marketing of 3G. *Marketing Intelligence & Planning, 21*(6), 370-378.
Satorra, A. (1989). Alternative test criteria in covariance structure analysis: A unified approach. *Psychometrika, 54*, 131-151.
Scarpi, D., Pizzi, G., & Matta, S. (2022). Digital technologies and privacy: State of the art and research directions. *Psychology & Marketing, 39*(9), 1687-1697.
Shanahan, T., Tran, T. P., & Taylor, E. C. (2019). Getting to know you: Social media personalization as a means of enhancing brand loyalty and perceived quality. *Journal of Retailing and Consumer Services, 47*, 57-65.
Sheng, H., Nah, F. F. H., & Siau, K. (2008). An experimental study on ubiquitous commerce adoption: Impact of personalization and privacy concerns. *Journal of the Association for Information Systems, 9*(6), 1.
Shin, W., & Lin, T. T. C. (2016). Who avoids location-based advertising and why? Investigating the relationship between user perceptions and advertising avoidance. *Computers in Human Behavior, 63*, 444-452.
Singh, N., Jain, M., Kamal, M. M., Bodhi, R., & Gupta, B. (2024). Technological paradoxes and artificial intelligence implementation in healthcare: An application of paradox theory. *Technological Forecasting and Social Change, 198*, 122967.
Smink, A. R., Van Reijmersdal, E. A., Van Noort, G., & Neijens, P. C. (2020). Shopping in augmented reality: The effects of spatial presence, personalization and intrusiveness on app and brand responses. *Journal of Business Research, 118*, 474-485.
Strycharz, J., Van Noort, G., Smit, E., & Helberger, N. (2019). Protective behavior against personalized ads: Motivation to turn personalization off. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace, 13*(2).
Sun, Y., Wang, N., Shen, X. L., & Zhang, J. X. (2015). Location information disclosure in location-based social network services: Privacy calculus, benefit structure, and gender differences. *Computers in Human Behavior, 52*, 278-292.
Syam, N., & Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management, 69*, 135-146.
Tanner, C., & Wölfing Kast, S. (2003). Promoting sustainable consumption: Determinants of green purchases by Swiss consumers. *Psychology & Marketing, 20*(10), 883-902.
Thomaz, F., Salge, C., Karahanna, E., & Hulland, J. (2020). Learning from the dark web: Leveraging conversational agents in the era of hyper-privacy to enhance marketing. *Journal of the Academy of Marketing Science, 48*, 43-63.
Tran, T. P., Van Solt, M., & Zemanek, J. E. (2022). How does personalization affect brand relationship in social commerce? A mediation perspective: An abstract. In *Developments in marketing science: Proceedings of the Academy of Marketing Science* (pp. 535–536).
Tran, T. P., Lin, C. W., Baalbaki, S., & Guzmán, F. (2020). How personalized advertising affects equity of brands advertised on Facebook? A mediation mechanism. *Journal of Business Research, 120*, 1-15.
Unni, R., & Harmon, R. (2007). Perceived effectiveness of push vs. pull mobile location-based advertising. *Journal of Interactive Advertising, 7*(2), 28-40.
Vimalkumar, M., Sharma, S. K., Singh, J. B., & Dwivedi, Y. K. (2021). 'Okay Google, what about my privacy?': User's privacy perceptions and acceptance of voice-based digital assistants. *Computers in Human Behavior, 120*, 106763.
Wai, K., Dastane, D. O., Johari, Z., & Ismail, N. B. (2019). Perceived risk factors affecting consumers' online shopping behavior. *The Journal of Asian Finance, Economics and Business, 6*(4), 246-260.
Wang, T., Duong, T. D., & Chen, C. C. (2016). Intention to disclose personal information via mobile applications: A privacy calculus perspective. *International Journal of Information Management, 36*(4), 531-542.

Wiese, M., Martínez-Climent, C., & Botella-Carrubi, D. (2020). A framework for Facebook advertising effectiveness: A behavioral perspective. *Journal of Business Research, 109*, 76-87.

Wottrich, V. M., van Reijmersdal, E. A., & Smit, E. G. (2018). The privacy trade-off for mobile app downloads: The roles of app value, intrusiveness, and privacy concerns. *Decision Support Systems, 106*, 44-52.

Xu, H., Dinev, T., Smith, J., & Hart, P. (2011). Information privacy concerns: Linking individual perceptions with institutional privacy assurances. *Journal of the Association for Information Systems, 12*(12), 1.

Xu, H., Luo, X. R., Carroll, J. M., & Rosson, M. B. (2011). The personalization privacy paradox: An exploratory study of decision-making processes for location-aware marketing. *Decision Support Systems, 51*(1), 42-52.

Xu, H., Oh, L. B., & Teo, H. H. (2009). Perceived effectiveness of text vs. multimedia location-based advertising messaging. *International Journal of Mobile Communications, 7*(2), 154-177.

Zanker, M., Rook, L., & Jannach, D. (2019). Measuring the impact of online personalization: Past, present, and future. *International Journal of Human-Computer Studies, 131*, 160-168.

Zeng, F., Ye, Q., Li, J., & Yang, Z. (2021). Does self-disclosure matter? A dynamic two-stage perspective for the personalization-privacy paradox. *Journal of Business Research, 124*, 667-675.

Zhao, L., Lu, Y., & Gupta, S. (2012). Disclosure intention of location-related information in location-based social network services. *International Journal of Electronic Commerce, 16*(4), 53-90.

Zhu, H., Ou, C. X., van den Heuvel, W. J. A., & Liu, H. (2017). Privacy calculus and its utility for personalization services in e-commerce: An analysis of consumer decision-making. *Information & Management, 54*(4), 427-437.