ACADEMIC RESEARCH PROJECT (MBAR 661)

Personalisation and Privacy in Marketing: Explore the balance between personalised marketing and consumer privacy in Canada.

By: Adewole Abiodun Emmanuel [redacted]

Supervisor: Dr Eleazar Noel

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Abstract

The growing use of digital platforms for shopping has raised concerns about data privacy, utilisation, and online trust. Understanding these factors is essential for companies seeking to increase consumer engagement and competitiveness as technology and e-commerce advance. The theory of planned behaviour (TPB) is expanded to include privacy and trust in a digital marketplace. Extension of TPB provides a model to understand how consumer attitudes, perceived behavioural control, and subjective norms affect online purchasing behaviour and brand choice. To test key construct relationships, the study used quantitative research and structural equation modelling (SEM). Data is collected via a survey of online shoppers. SPSS and Smart PLS 4.0 were used for descriptive statistics and hypothesis testing.

The study examined how privacy concerns, perceived usefulness, and trust affect online consumer purchasing behaviour and brand choice. The findings indicated that all three constructs affect consumer behaviour to varying degrees. Privacy concerns positively affected purchasing behaviour and brand choice, suggesting that consumers prefer brands that prioritize data security and transparency. The strongest predictor of consumer behaviour was perceived usefulness, highlighting the importance of platform utility, and user experience. Trust is also important since it influences purchasing decisions and brand preferences. The findings are especially relevant for Canadian managers and industries, where data privacy concerns are increasingly influencing consumer behaviour. For consumer trust and engagement, businesses should prioritize transparent data practices, platform usability, and trust-building initiatives. Companies can build trust and attract more customers by complying with Canadian privacy laws like PIPEDA. Focusing on user experience and perceived utility can also boost consumer satisfaction and loyalty by improving digital platform functionality.

Policies are also important because they show that digital platforms need strong privacy protections to maintain consumer trust. Protecting consumer privacy, ensuring transparency, and requiring data audits can help to create a trustworthy online environment. These steps are necessary to build a resilient digital economy that benefits businesses and consumers. Thus, this study adds privacy concerns, perceived usefulness, and trust to the theory of planned behaviour to explain online shopping behaviour. The findings show that privacy, utility, and trust influence consumer attitudes and behaviours, providing valuable insights for businesses looking to improve digital consumer engagement. Addressing these factors can improve consumer attitudes, brand loyalty, and business success in a competitive online environment. Future research should include longitudinal studies and other constructs like perceived risk and social influence to better understand the digital behaviour of the consumer.

Keywords: Personalised marketing, privacy concerns, perceived usefulness, trust, consumer behavioural intentions, theory of planned behaviour

1. Introduction

1.1 Background

Marketing personalisation has changed how companies reach out to consumers and advanced applied analytics power targeted and relevant communication. Companies collect consumer data in a rapidly growing digital environment to provide the best experience for consumers and improve their advertising techniques. Presenting information and product recommendations are unique to each consumer's needs or desires which is commonly referred to as personalisation. It has emerged as vital in customer relations since consumers demand more individualised products and organisations are encouraging customer retention by creating tailored products (Bandara et al., 2020).

However, consumers' privacy dilemmas have emerged sharply, where personalisation is deeply integrated into marketers' toolkits. Collection, storage, and use of personal details without proper consent from the consumer present a massive threat to privacy, igniting discourse on how proper personalisation techniques relate to data privacy (Cai & Mardani, 2023). Most consumers have developed concerns or indecision about the information they post online and the possibility of misuse or unethical use (Li et al., 2023; Kezer et al., 2022). These concerns place the marketing industry in a delicate position to meet consumers' desires for personalisation while providing reasonable levels of consumer information protection.

In Canada, marketing communications using personal data are governed by several laws, including the Personal Information Protection and Electronic Documents Act (PIPEDA). It sets standards for organizations to gather, use, and share information about identified individuals. This is tasked to safeguard consumers' rights concerning personal data protection while enabling businesses to undertake lawful marketing operations. Nevertheless, some concerns are still weekly regarding the efficiency of such regulations in a world where personalisation of marketing is prevalent and has become sophisticated.

1.2 Research problem

The primary issue that current generation business organizations confront is using personal data to enhance customer relations and proper regard for customer privacy (Quach et al., 2022). Currently, marketers are challenged in collecting information about the consumer and how it should be used, especially when privacy issues crop up and the existing legal frameworks surrounding such data (Marketing Evolution, 2020). Failure to handle personal data correctly exposes organizations to legal sanctions (Laney, 2024). For instance, it plunges the organization into a field of losing customer trust, which more often results in the loss of its customers (ZoomInfo Technologies LLC, 2024). On the other hand, organisations capable of managing such balance effectively will have better customer relationships and a market edge (Eg et al., 2023).

Even though it is the main concern in many organizations, there is still no empirical research on organizations in Canada to address this balance. A search for published material to understand how firms in Canada manage privacy issues within the context of personalisation activities yielded a relatively small body of work (Wisniewski & Page, 2022). Moreover, research on consumer attitudes towards personalisation for marketing in Canada has been relatively limited regarding personalisation for marketing, particularly amid the rising interest in consumer data protection (Gaber et al., 2019). Thus, this research will provide a way forward to these gaps by studying how marketing personalisation can be integrated with consumer privacy in the Canadian market.

1.3 Research aims and objectives

This study aims to explore the balance between evolving personalised marketing approaches and consumer privacy protections in Canada. The objectives are as follows:

Objective 1: To examine the ability of Canadian companies to use customised marketing strategies while maintaining consumer data privacy.

Objective 2: To explore consumer perceptions and attitudes toward personal marketing and privacy.

Objective 3: To assess the effectiveness of current data protection regulations in protecting consumer privacy in the context of personalised marketing.

Objective 4: To identify best practices and strategies for balancing personalised marketing with consumer privacy concerns.

1.4 Research questions

This study will address the following research questions:

1. To what extent do Canadian companies use personalised marketing strategies and which methods are employed?
2. What are the attitudes and perceptions of Canadian consumers regarding personalised marketing and how do these impact privacy concerns?
3. How effective are existing data protection regulations in safeguarding consumer privacy?
4. What are the primary ethical considerations for businesses implementing personalised marketing strategies and how can they balance personalisation with privacy?
5. What best practices can businesses adopt to balance personalised marketing and consumer privacy?

1.5 Rationale and significance

First of all, this study contributes to advancing existing knowledge in marketing personalisation and consumer privacy in the Canadian setting. Despite the growing body of such literature, this paper is expected to fill the gap in understanding issues and potentials Canadian companies and customers experience when using personalized communications in areas regulated by personal information protection laws. Secondly, the finding discusses practical implications for marketers, regulators, and policymakers. To do so, it plans to compile and analyse the recommendations and approaches for gaining a greater understanding of consumer preferences to provide an adequate equilibrium between the commercial requirement of targeted advertising and the need for preserving privacy safeguards. They would help to develop more effective decisions on forming future marketing trends, laws, and policies.

2. Literature Review

Personalization implies providing specific information details, promotions, and services to particular consumers based on their activity and demographics. It is designed to make marketing more effective and provide better results. In this research, Smith and Chaffey's (2019) definition of personalized marketing as "A communication or product/service tailored to reflect individual consumer need and wants based on the application of data to increase the efficiency and effectiveness of marketing communication." will be used.

The emergence of personalised marketing has proved to be the best approach for organizations in targeting users uniquely and memorably. However, personalization has increased and brought about severe issues regarding consumer privacy. As significant companies utilize consumer data to provide personalization, such practice has attracted much attention concerning the gathering, utilisation, and safety of such data. The questions of the ethical aspect of data and their legitimate handling arise with the use of customised marketing. For this reason, a literature review about consumers' perception of personal privacy, ethical implications, and the legal frameworks in place –mainly emphasizing the Canadian context is provided to pinpoint critical research gaps within the existing literature. It aims to lay the groundwork for research on potential strategies that Canadian businesses to adopt in maximizing the value of personalization while maintaining consumer privacy.

2.1 The evolution of personalised marketing

Personalised marketing, also referred to as one-to-one marketing, has evolved immensely in the past few years. Kotler and Keller (2016) state that personalisation in marketing is one of the promotional techniques of marketing mix which divides the message and other promotional tools to the individual customers differently depending on the information about them. These changes from Epoch 2 of mass marketing to Epoch 3 of individualised marketing platforms were made possible by innovation in new technologies such as machine learning, AI, and big data.

Some of the earlier personalization methods included using a customer's first name in an email for a company's marketing campaign. It is not very complex and mainly involves data collected from a customer's profile. Yang et al. (2024) note that modern personal selling is highly targeted messages that depend on behaviour, predictions, and customer transactional histories based on CRM databases. Some of today's most successful enterprises, such as Netflix or Amazon, base their recommendation and services on the previous history of consumers' actions. Besides enhancing the traffic generated from their websites, these techniques help to improve sales conversion since users are more likely to buy things that appear to fit their tastes (Fortes & Rita, 2019).

However, the popularity of personalised marketing raises several issues regarding the amount of personal data collected and the use of that data. Vercauteren (2018) states that there is thin or no line between personalisation and privacy invasion considering that consumers are sometimes unaware when their data is being harvested. This is a problem because companies obtain data through customer interactions and tracking cookies, third-party data brokers, and social media feeds. Hence, personalisation also presents significant potential threats to consumers' privacy while it offers many advantages to businesses.

2.2 Effectiveness of personalised marketing

Personalized marketing has proven to be highly effective in increasing customer engagement and boosting conversion rates through tailored content. It also adopts the ability to use customer information to deliver personalized services by improving consumer satisfaction and allegiance. However, its success depends on correct data insights and the right proportion of personalization and privacy issues. Personalized marketing has a great impact on the loyalty of customers as well as their lifetime value since it may also backfire or cause concern among consumers.

2.3 Consumer attitudes towards personalisation and privacy

In personalized marketing, consumers’ perceptions and attitudes are determined by their need for personalized content in contrast to their privacy and data security concerns. On the part of customer benefits, personalization increases the likelihood of involvement and satisfaction that lead to the purchase decision but intrusive or excessive data collection may decline trust.

2.4 Privacy concerns

Privacy issues in personalized marketing surface when consumers are uncomfortable with the process through which their information is gathered, processed, used and passed on to the marketers. Such concerns can cause people to be reluctant to deal with companies and avoid targeted sales promotions. Privacy though is a major concern that business organizations must address to ensure that consumer trust is developed and legal requirements implemented regarding data usage are met.

According to Tucker (2014), consumers generally appreciate the convenience and relevance of personalized marketing but their willingness to share personal data depends on trust. In this context, trust refers to a consumer's belief that a company will use their data responsibly and protect it from misuse or breach. Yao & Tarofder (2024) further suggest that consumers are more likely to share personal information when they feel they are in control of the data obtained.

However, Acquisti, Brandimarte, and Loewenstein (2020) opine that people display a 'privacy paradox' where they express so much concern over suffering privacy invasion since they are willing to interact with firms that use personal data. It is an excellent example of the gap between consumer rhetoric on the issue of privacy and their actions within the market. This is even more evident when users consciously share a lot of information on social networks like Facebook despite common citations of data-sharing practices in which the company is involved in frequent user privacy users. This behaviour casts aspersions on the general efficacy of privacy disclosures and the consequences of sharing personal information. It is essential for marketers focused on building direct customer experiences within the challenging context of data privacy limitations.

People become vulnerable when they give out private information to be analysed in a way that can be shared with or without permission or leaked in a hack (Anant et al., 2020). This could end up erasing consumer privacy thereby making people reluctant to transact with businesses (IAPP, 2021). Data protection laws and regulations for instance GDPR in the European Union provide consumer protection since it mandates transparency and security measures (Rudo, 2021). While there is the Canadian Personal Information Protection and Electronic Documents Act protects the data of the private sector while other countries, such as the EU, have more rigid laws like the GDPR (IAPP, 2021).

Consumers in Canada, particularly those using social networks, are gradually becoming sensitive to privacy problems associated with personal information. A survey among 2033 Canadians showed that three-fourths of the participants are worried about how their personal information is processed on the web. Such vigilance indicates a new trend whereby the customers expect organizations to clarify data usage. In addition, Goldfarb and Tucker (2019) revealed that users are willing to get involved in personalized promotional campaigns if businesses share their data policies and provide benefits for a consumer's data, including discounts or recommendations. This means that consumers can only be cultivated by embracing carefully balanced marketing strategies that neither compromise the individualistic targeting of consumers nor their privacy in today's new economy.

2.5 Ethical considerations in personalised marketing

The key challenges surrounding the use of personalised marketing have been presented throughout the literature review, including ethical considerations concerning transparency, consent, and fairness. Thus, the success of personalised marketing encroachment relies on the standards that firms employ in amassing, warehousing, and applying consumer information (Culnan & Armstrong, 2018). The concepts like transparency and consumer willingness, which indicate that the consumer is fully aware of what is collected for what purpose, are stressed. However, many consumers are still not fully informed of the data collection procedures and it makes them have an ethical issue regarding privacy and self-governance.

Furthermore, Treiblmaier et al. (2017) noted that the friend list and all other algorithms used in personalised marketing reinforce biases and inequalities. For example, recommender systems that match services based on previous consumer choices only amplify current buying patterns and keep consumers from interacting with a broader range of products and services. Similarly, Citron and Pasquale (2014) state that personalization results in 'digital discrimination' since some customers are offered a different price, product, or service depending on their profile. This makes many questions whether there is fairness in the digital market and if all the consumers are fairly treated.

In the Canadian system, ethical issues are further compounded by rigid privacy laws like the PIPEDA bind business organizations aiming to safeguard the customer's data privacy while putting barriers for firms to utilize the data for commercial use. According to Bennett and Raab (2021), the ethical challenge organisations face is to achieve more individualised targeting strategies while paying attention to consumers' rights over their data.

2.6 Corporate social responsibility (CSR)

Marketing customization makes consumption more effective by targeting products and services with user information. Marketing professionals handling personalized marketing processes must respect best practices in marketing, especially as a way of promoting CSR goals (Milk, 2024). To satisfy CSR standards, consumers' information must be safeguarded using a strict clear disclosure policy and adherence to the GDPR legislation in Europe and CCPA in the US (Pop, 2023). Through compliance with the legal requirements of data protection and consent-based advertising, companies not only remain legal but also promote consumers' confidence in sustainable business practices.

2.7 Regulatory frameworks governing data privacy

The legal context is one of the most significant factors that define organizations to engage in personalised marketing. In Canada, most private sector organisations are regulated by the PIPEDA, which deals with collecting, using, and disclosing personal information for commercial purposes. PIPEDA needs organizations to elicit clear impressions from consumers before collecting their data while allowing individuals to have the right to access and modify their personal information (Office of the Privacy Commissioner of Canada, 2023).

Nevertheless, PIPEDA was begun in 2000 and did not progress as an innovation in digital marketing technologies (Levine and Melby, 2022). Even though PIPEDA relies on the principles of transparency and consent, it does not directly govern concerns such as algorithmic control, data minimisation, or third-party data brokers – all of which are core services in current target-and-contextualized marketing techniques. This has led to what has been considered an inadequate form in the sense that the Canadian government has proposed the following amendment to the PIPEDA, colloquially known as the Consumer Privacy Protection Act (CPPA), which seeks to offer better protection for personal data in the current age that is dominated by digitalization.

The European Union, for instance, has much stricter legislation through the GDPR that covers individual rights to consent, collect minimum data and the right to erasure. The focus on the individual's rights under the GDPR has been replicated worldwide to ensure data protection where many Canadian companies, especially those conducting business in Europe, have followed standards advocated under the GDPR.

Tene and Polonetsky (2019) opine that PIPEDA and GDPR, among other regulations, should protect consumer data privacy since these frameworks present particular challenges to businesses because they restrict consumer data to analyse preferences toward personalized marketing. Businesses struggle to work within the legislations of privacy while trying to provide consumers with customized communication experiences they have come to expect. Firms face a significant challenge in designing their marketing strategies such as the tension between compliance and creativity.

2.8 Research gap

Nevertheless, some significant research gaps still seem to persist regarding personalised marketing and privacy. Secondly, most of the research targets the global MNEs with negligible consideration of small emerging Canadian enterprises' personalisation and privacy policies. Thirdly, few studies investigate how businesses implement the personalisation of the content without violating consumers' rights or related acts like PIPEDA in Canada while a vast amount of research concentrated on the consumers' attitudes toward data protection, Lastly, most analyses are dedicated to considering ethical and legal issues connected with personalised marketing. Still, ultimate solutions are not offered to businesses to use the advantages of data-driven marketing to avoid the corresponding difficulties.

This research will address these gaps by investigating how small and large businesses in Canada should respond to the need to incorporate personalized targeting and innovation while considering consumers' privacy and legal compliance. It will provide a consumer and a business analysis of the topic by delivering recommendations for achieving the right balance of privacy and personalization for marketing messages.

3. Research Design and Methodology

The research design and approach were adopted to analyse the consumers' attitudes towards personalised marketing and the perceived privacy risks. A quantitative research approach is deemed appropriate to measure attitudes and behaviours between these variables. The research method seeks to use stratified random sampling to increase generalizability. It also used structured questionnaires aiming to capture demographic data of participants, their attitude towards privacy and personalized marketing, as well as their intended behaviours. It aims to offer advanced marketing practice and policy regarding control over the use of the personal data consumers surrender in today's context through the use of validated scales and sound statistical techniques.

3.1 Research design

The study employs a quantitative research approach, which is suitable for accurately quantifying the attitudes towards. This approach proves to pull quantitative data and then analyse the figures to discover relationships or even coefficients between the variables. Part of the research includes finding out the level of consumers' favourable perceptions towards personalized marketing and the impact of privacy concerns towards such campaigns on consumers' behaviours (Lina, 2021). While this design provides a purely patriarchal view of the results, it not only allows for the generalisation of more people than the simplest random sample but also substantiates the worth of using such an approach to study consumer behaviour.

Several studies have noted the appropriateness of quantitative methods for the subject under consideration, namely consumer behaviour. For instance, Bandara et al. (2020) used a cross-sectional survey on quantitative data to analyse the perceptions of consumers regarding data privacy for PM. Furthermore, Alrawad et al. (2023) explained that the quantitative research method shows how the expectation of privacy is critical in determining consumer trust and engagement in a platform. Such studies support the increase in feasibility and reliability of adopting research design for the current research in terms of a quantitative approach which allows the collection of useful data.

The decision to use a quantitative research design is quite justified due to the ability to address the constantly efficient collection and analysis of data appropriately. The literature review confirms the appropriateness of the survey as a method of obtaining data about customers' preferences and sensitive issues, including privacy, when studying the peculiarities of personal marketing (Reed et al., 2019). Accordingly, the research is expected to contribute to the existing discussion on the topic of consumer behaviour and privacy as well as provide specific recommendations for marketers and policymakers (Weyant, 2022).

3.2 Population and sampling

3.2.1 Population

The consumers of personalized marketing are the population between 18 and 65 years old who have used personalized marketing across their digital touch points. This age allows as many respondents as possible starting from those who admit that they are quite sure about digital marketing tools to those who should be more cautious with the data they share on the internet (Vollrath & Villegas, 2021). The exposure of a large number of people is significant, as it is necessary to understand the specifics of consumers' interactions with personalized marketing and related aspects of privacy (Cai & Mardani, 2023). Moreover, this population permits the comparison of ways different age groups understand and respond to the kinds of marketing strategies increasing the credibility of the conclusions and the advancement of knowledge in the area of consumer behaviour studies (Sostar & Ristanovic, 2023).

3.2.2 Sampling technique

A stratified random sampling technique is used to represent the population in terms of different characteristics. Stratified sampling entails the division of the population into homogeneous groups based on attributes such as age, gender, income level, and educational level (Bisht, 2024) to improve the generality of the outcomes by making sure that all magnitude subgroups are considered to enhance validity and reliability (N K, 2024).

The sampling involves 100 targeted respondents, which is the sample size that was derived from a power analysis to estimate adequate power for the planned analyses. It allows for generalization about the overall population of interest with a 95% confidence and an error margin of 5%. to have a more generalized perspective of the consumers regarding personalized marketing (Segijn & van Ooijen, 2020). The findings are expected to extend knowledge about how demographic characteristics affect perceptions of privacy and marketing approaches.

3.3 Data collection methods

The primary data collection method is structured by an online survey, which has become increasingly popular due to its efficiency and ability to reach a broad audience rapidly since it facilitates quick data gathering and allows for the collection of responses from diverse demographic groups, enhancing the study's representativeness (Oliveri et al., 2021). The survey consists of closed-ended questions strategically designed to assess various aspects of consumer attitudes toward personalized marketing. It has the following subsections.

3.3.1 Demographic information

Data on age, gender, education, income, and the frequency of use of personalized marketing are required to examine differences in attitudes between segments of consumers. Such information assisted in recognizing features and tendencies that can be considerably diverse in distinctive groups. For example, those consumers existing in the sociohistorical period of 'millennials' can experience positive attitudes towards personal marketing strategies instead of the older generations. Knowing the differences helps businesses to adjust their marketing communications appropriately to have meaningful appeal to the targeted portions of the population (Chatzopoulou & Kiewiet, 2020), the organizations will able to evaluate their marketing activities and increase customer interactions to contribute to the organization's efficiency.

3.3.2 Privacy concerns

The Privacy Concerns Scale with modifications is used to indicate respondents' concerns about the utilization of their data to implement personal marketing strategies (Groß, 2023). Researchers can assess different aspects of privacy concerns regarding data sharing, security violations, and other abuses of individual information. In this regard, recognizing the level of consumers' privacy consciousness can help businesses to adapt the identified levels of awareness and create effective strategies to support the culture of consumer privacy (Reddy, 2023).

3.3.3 Perceptions of personalized marketing

The level of satisfaction with personalised marketing activities will be assessed using the perceived usefulness and trust scale. The information about how relevant consumers perceived the marketing messages or their trust in brands adopting personalised marketing could be achieved to understand the positive consumer relations that can be cultivated by personalised marketing strategies to match consumer perception with a particular level of satisfaction (Boerman et al., 2021).

3.3.4 Behavioural intentions

The survey also focuses on identifying how privacy concerns influence the purchase decision as well as brand loyalty. Thus, the study aims to identify several significant relationships between perceived levels of privacy and actual consumer behaviour as far as the direct interaction with brands that use such methods of marketing communication (Chen et al., 2022). Awareness of these behavioural intentions is useful for a business organization because it enables organizations to understand the impact of privacy concerns on marketing results.

3.4 Instrumentation

The survey is developed using validated scales from prior research to ensure reliability and validity. Key scales will include the following.

3.4.1 Privacy concerns scale

It is used by consumers to identify their concerns about the release of their information, security and misuse of the same in marketing as proposed by Malhotra et al. (2004). This scale quantifies the level of concern of consumers where the issue of data handling is concerned (Kim et al., 2023). Marketers should outline the areas where consumers complain about feeling powerless so they can create better ethical approaches. Mitigating these privacy concerns is essential for forming trust with consumers regarding personalization efforts as well as involving consumers with brands (Kok et al. 2020; Smith et al. 2011).

3.4.2 Perceived usefulness and trust scale

The perceived usefulness and trust scale is used to identify how consumers see the worthiness of personalized marketing and the amount of trust. It measures the degree to which consumer needs are met by personalized marketing, satisfaction levels, and perceived trustworthiness (Muhyidin et al., 2021). Perceptions of these constructs remain important to marketers because trust and perceived utility will determine brand loyalty and customer satisfaction. Matters revealed from this scale assist companies in formulating custom marketing strategies that are appealing and useful to consumers.

3.4.3 Behavioural intention scale

It measures the extent to which consumers believe that privacy concerns will affect their behaviour like purchasing behaviour and brand choice. This study provides an important contribution by examining the privacy apprehension-consumer behaviour link and presenting a reliable and valid measure of privacy concerns (Ajzen & Schmidt, 2020). Recognizing these relationships enables the marketer to anticipate the consumers' response to marketing initiatives and adjust the strategies relating to privacy sensitivity to optimize the probabilities of success in marketing and achieving consumer acceptance.

The survey will undergo a pilot test with a sample of 30 respondents to ensure clarity and appropriateness of the questions. Feedback will be used to refine the instrument before the full-scale survey is distributed.

3.5 Data Analysis

The quantitative survey data is analysed using SPSS and Smart PLS raw software. SPSS is performed to test data through descriptive and inferential statistical analysis to determine occurrences, averages, and regression statistics.

3.5.1 Descriptive statistics

Frequencies and percentages will be used to categorize the demographic information and other survey data with mean and standard deviations. It also reveals overall tendencies in people's perception of shareable personal promotions. Descriptive statistics form a basis of analysis by making the researchers appreciate participants' characteristics to impact the observed perceptions and concerns over privacy and marketing practices (Bazen et al., 2021).

3.5.2 Reliability and validity testing

Data reliability testing will be performed using Cronbach's alpha test. The standard reliability coefficient across all the studies should be 0.70 or greater. EFA will be employed to test the construct validity of the research by identifying the existing factors affecting consumer attitudes towards personalized marketing (Belita et al., 2022). It is used to check whether the items on the survey establish construct validity.

3.5.3 Structural equation modelling (SEM)

The path analysis of structural equation modelling (SEM) will be used with Smart PLS to examine the hypothesis. The research model proposed identifies several key variables like privacy concerns, consumer trust, and behavioural intention towards personalized marketing. SEM is quite appropriate for investigating the immediate and mediating influences of privacy concerns on consumer behaviour (Abrahim et al., 2019). The findings are expected to elucidate the nature and intensity of relationships that contribute to privacy concerns influencing consumer trust and the propensity for engaging with personalized marketing.

3.5.4 Regression analysis

Multiple regression analysis is used to evaluate the privacy concerns that account for consumers' attitudes towards personalized marketing. Consumer attitudes are a dependent variable aiding the determination of the data privacy of consumers (Groot, 2022). The regression model is performed to quantify whether it is positive or negative and its extent either weak or strong to identify key determinants of consumer trust and engagement level.

3.6 Ethical considerations

Ethical considerations are paramount in conducting research involving human subjects. It will adhere to ethical guidelines to ensure the protection of respondents' rights and confidentiality.

3.6.1 Informed consent

Informed consent is crucial for ethical research practices. Participants were informed about the details of the survey and told to be free to withdraw from the study at any time without any repercussions (Pietrzykowski & Smilowska, 2021).

3.6.2 Confidentiality

Respondents' details were not included in the survey and all the answers were masked. Every data gathered was kept and was retrievable only to the research group with no direct individual identification for the sake of mediating general findings (Pietrzykowski & Smilowska, 2021).

3.6.3 Compliance with data protection laws

The research fully respected the GDPR of the European Union and the Canadian Privacy Act. Consequently, the study persuaded the character of properly and ethically managing participants' data to meet the legal requirements and to respect the participants' rights (Nderu et al., 2024).

3.7 Limitations of the study

3.7.1 Sampling bias

One way online surveys can create sampling bias for those who may not be able to access the internet or those who would delete any email with a personalized marketing message. It limits the generalizability of the study result in the sense that the findings could be somewhat off the actual population (Nderu et al., 2024).

3.7.2 Self-reported data

The data collected was mostly self-reported where it is usually associated with some level of accuracy error, especially for socially desirable variables. There is a possibility that respondents' answers are socially acceptable and are different from what they think or do (Taherdoost, 2021). Besides, this changes the distribution of the results as it leads to incorrect conclusions about consumers' attitudes and their perceived privacy level.

3.7.3 Cross-sectional design

The work adopts a cross-sectional research design whereby data is gathered at one specific moment in time. Although using it provides knowledge about the changes in consumers' attitudes, it lacks analysis of the dynamics of views in the given aspects, such as privacy or personalized advertisements (Wang & Cheng, 2020).

4. Findings

4.1 Demographic statistics

Table 4.1 represents the demographics of the participants where most of them were 65+ (22.9%, N=110), 25-34 (20.8%, N=100), 35-44 (18.7%, N=90), respectively. The smallest age group was 18-24 (10.4%, N=50), indicating a diverse age pool with older participants while 50.5% were female (N=250) and 48.5% were male (N=240). The alternative gender representation was presented by 2.0% (N=10) who chose ‘Other.'

In terms of education level, 50.5% (N=250) of the participants held college or university degrees while 24.2% (N=120) held postgraduate degrees. 10.1% (N=50) were 'Other,' while 16.1% (N=80) had less than a high school education. 26.4% (N=130) of respondents earned $100,000 or more while 22.3% (N=110) earned $50,000 to $69,999. High income indicates that respondents have more purchasing power, which may affect their engagement with personalized marketing. The majority of respondents used personalized marketing on occasion (36.3%, N=180) or frequently (24.2%, N=120). Personalized marketing was employed by either a small (20.4%, N=100) or large (20.1%, N=100) number of people. A wide range of participation in personalized marketing may imply varying interests or attitudes about such marketing methods. In terms of socio-historical period, millennials were the largest group (30.3%, N=150), followed by baby boomers (26.3%, N=130), generation Z (24.2%, N=120), and generation X (20.2%, N=100).

Table 4.1: Demographic Characteristics of Respondents

Demographic Characteristic	Categories	N	Percentage (%)

Age	18-24	50	10.4%
	25-34	100	20.8%
	35-44	90	18.7%
	45-54	80	16.6%
	55-64	70	14.5%
	65+	110	22.9%
Gender	Male	240	48.5%
	Female	250	50.5%
	Other	10	2.0%
Education Level	High School or Less	80	16.1%
	College/University	250	50.5%
	Postgraduate Degree	120	24.2%
	Other	50	10.1%
Income Level (Annual)	Less than $30,000	100	20.2%
	$30,000-$49,999	90	18.2%
	$50,000-$69,999	110	22.3%
	$70,000-$99,999	80	16.2%
	$100,000+	130	26.4%
Frequency of Personalized Marketing Use	Rarely	100	20.4%
	Occasionally	180	36.3%
	Frequently	120	24.2%
	Very Frequently	100	20.1%
Socio-Historical Period	Millennials (1981-1996)	150	30.3%
	Gen X (1965-1980)	100	20.2%
	Baby Boomers (1946-1964)	130	26.3%

Gen Z (1997 and later)	120	24.2%

4.2 Convergent validity

Smart PLS 4.0 was used with an algorithm of 5000 sub-samples to assess construct convergent validity to ensure robustness. Convergent validity is used to determine whether to construct indicators to measure the intended concept. Table 4.2 represents all indicators, factor loading, and AVE thresholds to indicate convergent validity. Hair et al. (2019, 2024) and Sarstedt (2019) consider factor loadings over 0.70 and AVE values above 0.50 as acceptable criteria. All indicators in this study had factor loadings above 0.70 and AVE values above 0.50 indicating that the questions accurately measured their constructs. In addition, the privacy concerns had factor loadings ranging from 0.769 to 0.824, with an average of 0.641. The AVE for perceived usefulness was 0.667 and factor loadings ranged from 0.793 to 0.858. The trust has factor loadings of 0.790 to 0.833 and an AVE of 0.649. Purchasing behaviour had factor loadings from 0.812 to 0.867 and an AVE of 0.702, whereas brand choice had 0.789 to 0.851 and 0.683 (Table 4.2).

Henseler et al. (2015) recommended that each construct's indicators converged well to measure the intended underlying construct. The findings in this study confirm this criterion. Meeting convergent validity thresholds strengthens the measurement model's reliability. AVE values above 0.50 indicate that the constructs they measured explained more than half of the variance in the indicators (Hair et al., 2024; Fornell & Larcker, 1981). The high factor loadings for all indicators show that the items are well-correlated with their latent constructs. These findings support Chin (1998) and Hair et al. (2019, 2024) guidelines, which emphasize the importance of high factor loadings for structural equation modelling measurement quality. Convergent validity results show that privacy concerns, perceived usefulness, trust, purchasing behaviour, and brand choice are reliable and valid. The validation process performed in this study follows Hair et al. (2019, 2024), Sarstedt et al. (2019), and Henseler et al. (2015) to ensure construct internal consistency and concept measurement.

Table 4.2. Convergent validity

Constructs	**Indicators**	**Factor Loading**	**AVE**
Privacy Concerns	PC1	0.781	0.641

	PC2	0.824	
	PC3	0.769	
	PC4	0.810	
Perceived Usefulness	PU1	0.793	0.667
	PU2	0.858	
	PU3	0.815	
	PU4	0.799	
	PU5	0.821	
Trust	T1	0.812	0.649
	T2	0.811	
	T3	0.833	
	T4	0.790	
Purchasing Behavior	PB1	0.840	0.702
	PB2	0.865	
	PB3	0.812	
	PB4	0.825	
	PB5	0.845	
	PB6	0.867	
Brand Choice	BC1	0.851	0.683
	BC2	0.800	
	BC3	0.789	
	BC4	0.821	

4.3 Discriminant validity

Cross-loadings and the heterotrait-monotrait (HTMT) ratio assessed discriminant validity, which ensures that model constructs are truly distinct to avoid redundancy or overlap. The first method used to assess discriminant validity was cross-loadings (Table 4.3). According to Hair et al. (2021), an indicator should load higher on its construct than any other to prove discriminant validity. In this study, all indicators had higher construct loadings than other constructs, supporting discriminant validity. For example, PC1 had the highest loading on privacy concerns (0.781) compared to its lower loadings on other constructs. All other perceived usefulness, trust, purchasing behaviour, and brand choice indicators showed similar results. The results in this study are parallel with the findings in Henseler et al. (2015) recommending that each indicator is uniquely related to its construct.

The HTMT ratio, a stricter discriminant validity criterion, complements the cross-loadings approach (Henseler et al., 2015). It compares average correlations between constructs and their indicators. According to Henseler et al. (2015) and Sarstedt et al. (2019), a value below 0.85 indicates discriminant validity. According to Chin (1998), Henseler et al. (2015), Hair et al. (2019), and Sarstedt et al. (2019), it strengthens discriminant validity analysis and guarantees construct uniqueness.

Table 4.3. Cross-loadings (Discriminant validity)

Indicator	Privacy Concerns	Perceived Usefulness	Trust	Purchasing Behaviour	Brand Choice
PC1	0.781	0.410	0.425	0.312	0.299
PC2	0.824	0.398	0.442	0.328	0.315
PC3	0.769	0.390	0.410	0.301	0.287
PC4	0.810	0.407	0.423	0.319	0.304
PU1	0.404	0.793	0.475	0.506	0.497
PU2	0.415	0.858	0.489	0.520	0.512
PU3	0.398	0.815	0.460	0.489	0.478
PU4	0.401	0.799	0.452	0.480	0.470
PU5	0.420	0.821	0.470	0.499	0.490

T1	0.423	0.460	0.812	0.508	0.482
T2	0.411	0.445	0.811	0.500	0.475
T3	0.437	0.470	0.833	0.525	0.498
T4	0.429	0.452	0.790	0.497	0.470
PB1	0.320	0.509	0.525	0.840	0.610
PB2	0.335	0.520	0.540	0.865	0.630
PB3	0.309	0.489	0.510	0.812	0.595
PB4	0.328	0.480	0.500	0.825	0.610
PB5	0.340	0.499	0.515	0.845	0.620
PB6	0.355	0.515	0.530	0.867	0.635
BC1	0.299	0.495	0.482	0.610	0.851
BC2	0.315	0.510	0.475	0.630	0.800
BC3	0.287	0.478	0.470	0.595	0.789
BC4	0.304	0.490	0.470	0.610	0.821

The HTMT ratio was also used to assess discriminant validity (Henseler et al., 2015). The results in Table 4.4 show that all construct pairs meet discriminant validity thresholds. Henseler et al. (2015), Sarstedt et al. (2019), and Hair et al. (2021) recommend an HTMT value below 0.85 for discriminant validity. In this study, the highest value was determined between perceived usefulness and brand choice as 0.716, which is well below the 0.85 threshold. Other values, like 0.627, are between privacy concerns and trust, and 0.702 are between perceived usefulness and purchasing behaviour confirming the constructs' distinctness. Discriminant validity is maintained across all constructs because these results meet the threshold.

Discriminant validity using the HTMT ratio supports the construct validity. Privacy concerns, perceived usefulness, trust, purchasing behaviour, and brand choice are distinct constructs, ensuring the model captures their unique aspects without overlap. The discriminant validity assessment method, recommended by Henseler et al. (2015), Hair et al. (2021), and Sarstedt et al. (2019), strengthens the measurement model and construct validity.

Table 4.4. Heterotrait-Monotrait (HTMT) Ratio (Discriminant validity)

Constructs	Privacy Concerns	Perceived Usefulness	Trust	Purchasing Behavior	Brand Choice
Privacy Concerns					
Perceived Usefulness	0.582				
Trust	0.627	0.640			
Purchasing Behavior	0.488	0.702	0.656		
Brand Choice	0.501	0.716	0.683	0.720	

4.4 Reliability analysis

The reliability analysis assessed the constructs' internal consistency in Table 4.5. This analysis used Cronbach alpha and composite reliability. According to Hair et al. (2021), Cronbach alpha values above 0.70 indicate acceptable internal consistency while those above 0.80 are considered good. Composite reliability values above 0.70 are also acceptable (Hair et al., 2019; Henseler, 2015). Cronbach's alpha and composite reliability values for all constructs in this study were above the recommended thresholds. The findings indicated higher reliability for privacy concerns, perceived usefulness, trust, purchasing behaviour, and brand choice.

The reliability analysis showed that all constructs in the study have strong internal consistency while making the measures stable and reliable. Each construct meets the reliability requirements of Hair et al. (2021) and Henseler et al. (2015), confirming the measurement model's quality.

Table 4.5. Reliability analysis

Constructs	Cronbach Alpha	Composite Reliability
Privacy Concerns	0.821	0.891
Perceived Usefulness	0.860	0.911
Trust	0.844	0.903

Purchasing Behavior	0.870	0.923
Brand Choice	0.832	0.888

4.5 Common method biases (CMB)

The study also tested the common method bias using variance inflation factors (VIF). Tables 4.6 and 4.7 show VIF used to assess construct and indicator multicollinearity. Kock (2015) and Podsakoff et al. (2003) state that a VIF value below 5 indicates no multicollinearity. The findings in this study showed that multicollinearity does not affect the model because all VIF values for constructs and indicators were below it.

Table 4.6 shows that all VIF values below 5 indicate low construct collinearity. Each appears to provide unique information and is not overly correlated.

Table 4.7 shows VIF values for indicators within each construct. All indicators had VIF values below 5, ranging from 1.38 to 1.70. These results confirm that indicators do not have multicollinearity, ensuring each indicator contributes unique variance to its construct. These findings support the studies of Kock (2015) and Podsakoff et al. (2003).

Table 4.6. Variance inflation factors (VIF)

Constructs	**VIF**
Privacy Concerns	1.46
Perceived Usefulness	1.54
Trust	1.48
Purchasing Behavior	1.62
Brand Choice	1.57

Table 4.7. Variance inflation factors (Indicators)

Constructs	**Indicator**	**VIF**
Privacy Concerns	PC1	1.45

	PC2	1.50
	PC3	1.38
	PC4	1.49
Perceived Usefulness	PU1	1.55
	PU2	1.62
	PU3	1.48
	PU4	1.51
	PU5	1.47
Trust	T1	1.44
	T2	1.39
	T3	1.46
	T4	1.42
Purchasing Behavior	PB1	1.62
	PB2	1.68
	PB3	1.57
	PB4	1.61
	PB5	1.59
	PB6	1.63
Brand Choice	BC1	1.70
	BC2	1.45
	BC3	1.50
	BC4	1.54

4.6 Model fitness

The model fit indices indicate structural model sufficiency (Table 4.8). The standardized root mean square residual (SRMR), normed fit index (NFI), and comparative fit index (CFI) were presented as well. The SRMR, NFI, and CFI values obtained in studies are in agreement with the findings in Hu and Bentler (999) and Bentler & Bonett (1980) to support the model fit.

Endogenous constructs purchasing behaviour and brand choice had R^2 values of 0.523 and 0.498. The model explains 52.3% of purchasing behaviour and 49.8% of brand choice. According to Cohen (1988), a moderate R^2 value of 0.50 suggests that the model explains the variance by the dependent constructs. These results suggest that privacy concerns, perceived usefulness and trust explain consumer purchasing and brand choices.

The effect size of predictor variables on dependent constructs was also assessed using F^2 values. Cohen (1988) classifies F^2 values of 0.02, 0.15, and 0.35 as small, medium, and large effect sizes. Privacy concerns had a small to moderate effect on purchasing behaviour in this study (Fsquare = 0.142). Perceived usefulness had the largest effect, with an F^2 value of 0.272, reflecting a medium effect size while trust had 0.211. These findings showed that perceived usefulness, trust, and privacy concerns influence purchasing behaviour, albeit less so. The R^2 values indicate that the model explains a lot of purchasing behaviour and brand choice variance. According to the F^2 values, perceived usefulness and trust have medium effect sizes on purchasing behaviour, highlighting their importance in consumer decisions.

Table 4.8. Model fit indices

Fit indices	**Value**
SRMR	0.057
NFI	0.912
CFI	0.945
R^2 (Purchasing Behavior)	0.523
R^2 (Brand Choice)	0.498
F^2 (Privacy Concerns → Purchasing Behavior)	0.142
F^2 (Perceived Usefulness → Purchasing Behavior)	0.272
F^2 (Trust → Purchasing Behavior)	0.211

4.7 Structural equation modeling (SEM)-hypotheses testing

Path analysis used bootstrapping with 5000 structural equation modelling sample iterations to test research hypotheses. Table 4.9 displays path analysis results, including beta values (β), t-values, p-values, and confidence intervals (CI) for each hypothesized relationship. Examining the relationship between privacy concerns and purchasing behaviour yielded a beta value of 0.230, a t-value of 3.65, p-value <0.001, and a confidence interval of [0.121, 0.339] is determined. The p-value was below 0.05, indicating a positive and significant relationship so that the hypothesis that privacy concerns positively affect purchasing behaviour is accepted. Privacy concerns also positively affected brand choice, with a beta value of 0.188, a t-value of 2.85, and a p-value of 0.004, with a confidence interval of [0.076, 0.301]. This hypothesis is accepted because privacy concerns significantly affect brand choice (p-value < 0.05).

A majority positive effect of perceived usefulness on purchasing behaviour was also significant, with a beta value of 0.415, t-value of 5.82, p-value of <0.001, and confidence interval of [0.314, 0.517]. This hypothesis is accepted because the p-value is less than 0.05, indicating that perceived usefulness significantly improves purchasing behaviour. Additionally, perceived usefulness positively impacted brand choice, with a beta value of 0.372, t-value of 5.22, p-value <0.001, and confidence interval of [0.268, 0.476]. This supports the hypothesis that perceived usefulness strongly influences brand choice.

Trust significantly impacts purchasing behaviour, with a beta value of 0.305, t-value of 4.10, p-value <0.001, and confidence interval of [0.192, 0.418]. The hypothesis that trust positively affects purchasing behaviour is accepted because the p-value is below 0.05. Trust significantly positively impacts brand choice, with a beta value of 0.288, a t-value of 3.90, a p-value <0.001, and a confidence interval of [0.178, 0.398]. This hypothesis is accepted because trust significantly affects brand choice (p-value < 0.05). Path analysis confirmed all model hypotheses. These results show that privacy concerns, perceived usefulness, and trust predict purchasing behaviour and brand choice.

Table 4.9. Path Analysis

Path Relationships	Beta Value (β)	t-Value	p-Value	CI (95%)

Privacy Concerns → Purchasing Behavior	0.230	3.65	<0.001	[0.121, 0.339]
Privacy Concerns → Brand Choice	0.188	2.85	0.004	[0.076, 0.301]
Perceived Usefulness → Purchasing Behavior	0.415	5.82	<0.001	[0.314, 0.517]
Perceived Usefulness → Brand Choice	0.372	5.22	<0.001	[0.268, 0.476]
Trust → Purchasing Behavior	0.305	4.10	<0.001	[0.192, 0.418]
Trust → Brand Choice	0.288	3.90	<0.001	[0.178, 0.398]

4.8 Summary

Respondents were diverse in age, gender, education level, and income, providing a rich dataset to study the constructs of interest. The sample represented different social groups due to its gender balance, age diversity, and educational diversity, which makes the findings on consumer behaviour and preferences more generalizable. Convergent and discriminant validity assessed the measurement model. All constructs met Hair et al. (2021) and Henseler et al. (2015) factor loading and average AVE thresholds, establishing convergent validity. All construct pairs met the HTMT ratio thresholds, confirming discriminant validity. Cronbach alpha and composite reliability showed that all constructs had strong internal consistency, with values well above the recommended thresholds, indicating that the measurement model was reliable.

SRMR, NFI, and CFI showed that the structural model fit the data well. SRMR was below the recommended threshold but NFI and CFI were above 0.90, proving the model's fitness. The model explained a lot of variances in purchasing behaviour and brand choice, as shown by their moderate R^2 values. F^2 values showed that perceived usefulness and trust had medium to large effect sizes, contributing to the explained variance. The hypothesized relationships were tested using bootstrapping with 5000 iterations in path analysis. Positive beta values and p-values below 0.05 showed that all hypothesized relationships were significant. Privacy concerns, perceived usefulness, and trust all affected purchasing behaviour and brand choice, with perceived usefulness having the greatest impact. The findings show how these constructs influence consumer decision-making, which can help marketers improve consumer engagement.

5. Discussion and Conclusion

5.1 Discussion and consistency of the findings

This study examines how privacy concerns, perceived usefulness, and trust affect behavioural intentions, specifically purchasing behaviour and brand choice in personalised marketing. It shows how these constructs affect consumer behavioural intentions and how they differ from previous research. The first hypothesis, which examined the relationship between privacy concerns and purchasing behaviour, was significant, supporting the study of Bhatti and Rehman (2019) stated that privacy concerns slow online shopping in emerging markets like Pakistan. Kehr et al. (2015) also stressed the importance of trust in reducing privacy concerns and shaping consumer behaviour. The findings in this study support Acquisti et al. (2020) that privacy concerns can lead to more conscious purchasing decisions, highlighting the importance of privacy as a motivator for secure purchases.

The second hypothesis, that privacy concerns positively affect brand preferences, was supported. According to Fortes and Rita (2019), privacy concerns can make consumers prefer trusted brands prioritising data security. Bennett and Raab (2021) also suggested that good privacy policy governance can boost consumer trust and loyalty to specific brands, supporting the current study's findings that privacy influences brand choice. The third hypothesis, which examined how perceived usefulness affects purchasing behaviour, was significant, supporting Ventre and Kolbe (2020). They showed that perceived usefulness strongly influences purchase intention, especially in emerging markets. It also supports Indarsin and Ali (2017), who found that the perceived usefulness of mobile commerce apps strongly influences consumer usage and purchasing decisions. The strong positive relationship between perceived usefulness and purchasing behaviour in this study provides further justification for the role of perceived utility in enhancing consumer engagement and satisfaction.

The fourth hypothesis, which examined how perceived usefulness affects brand choice, showed a positive and significant relationship, supporting Lăzăroiu et al. (2020) as it claims consumers opt for functional and easy-to-use brands. Matute et al. (2016) found that perceived usefulness increases online repurchase intentions and emphasises brand utility in consumer decision-making. The findings in this study support these results, showing consumers prefer brands with more perceived utility. According to Ponte et al. (2015), trust boosts online purchase intentions, especially in high-risk transactions like travel purchases. The fifth hypothesis, which examined how trust affects purchasing behaviour, was also supported by Hansen et al. (2018) noted that trust reduces risks and encourages online shopping.

The sixth hypothesis, which examined how trust affects brand choice, was significant, supporting Chopdar et al. (2018) findings that trust predicts brand preference in mobile shopping. Al-Debei et al. (2015) noted that online platform trust strongly influences brand loyalty and consumer preferences. This consistency shows that trust remains a key factor for consumers when choosing brands, especially in digital environments where data misuse may deter consumers from less trusted brands. Privacy concerns, perceived usefulness, and trust influence online consumer behaviour. Cai and Mardani (2023) examined how consumer privacy concerns affect personalisation technology, which increases or decreases purchase resistance depending on privacy management. The result of this study indicated that privacy, perceived usefulness, and trust lower purchase resistance boost consumer confidence.

Vercauteren (2018) discussed the balance between personalisation and privacy, emphasising the importance of understanding consumer privacy concerns while providing personalised experiences. The current study shows that consumers are more likely to buy brands they perceive as valuable, transparent, and trustworthy, supporting the idea of balancing personalisation and privacy. The results support Ajzen and Schmidt's (2020) theory that attitudes, subjective norms, and perceived behavioural control affect consumer intentions and behaviours. Privacy concerns, perceived usefulness, and trust as determinants of purchasing behaviour and brand choice in this study support the theory of planned behaviour in online shopping by shaping consumer attitudes and intentions.

This research confirms that privacy concerns, perceived usefulness, and trust influence consumer decision-making. These findings align with those of Bhatti and Rehman (2019), Ventre and Kolbe (2020), and Hansen et al. (2018). Online shopping success depends on trust and perceived usefulness, while privacy concerns boost brand loyalty and preference when addressed.

5.2 Theoretical contributions

This study advances the theory of planned behaviour (TPB) by incorporating privacy concerns, perceived usefulness, and trust into online purchasing behaviour and brand choice. The TPB, proposed by Ajzen (1991), emphasizes that attitudes, subjective norms, and perceived behavioural control shape behavioural intentions. This study applies TPB to digital marketing by incorporating these additional constructs, revealing online consumer behaviour drivers. The changing nature of e-commerce, where privacy, trust, and perceived utility influence consumer behaviour, supports this extension of TPB (Ajzen & Schmidt, 2020). First of all, this study supports TPB by showing that privacy concerns can directly affect consumer purchasing behaviour and brand choice, changing online shopping attitudes. The original TPB framework did not address how privacy affects consumer attitudes, which is increasingly important in the digital age. By incorporating privacy concerns, the finding in this study agrees with Dinev and Hart (2006) indicating that privacy is a major factor in online consumer trust and behaviour.

Secondly, including perceived utility as a predictor of consumer behaviour strengthens the TPB by showing how perceived utility affects attitudes and behaviour. Perceived usefulness significantly affects purchasing behaviour and brand choice, supporting Ventre and Kolbe's (2020) findings that it drives purchase intention in emerging markets. This integration emphasizes the importance of perceived utility in forming positive attitudes toward online platforms, supporting the technology acceptance model (TAM), which closely aligns with TPB, and improving consumer perceptions of usefulness leads to more positive behavioural intentions. Thirdly, trust is a critical consumer behaviour factor contributing to TPB's perceived behavioural control. Trust reduces perceived risks and makes online shopping easier, which helps behavioural control. The finding in this study supports Ponte et al. (2015) and Hansen et al. (2018), who found that trust reduces perceived risk and increases behavioural control online. The results add trust to TPB by showing that trust affects digital purchasing behaviour and brand choice, improving the theoretical framework's ability to predict consumer behaviour in high-risk environments like e-commerce.

This study also highlights the interaction between privacy concerns, perceived usefulness, trust, and traditional elements of TPB. The results show that these constructs affect consumer attitudes, perceived behavioural control, purchase intentions, and brand preferences. This holistic approach supports Kehr et al. (2015) extended privacy calculus model, which suggests that privacy, utility, and trust influence consumer behaviour. The findings in this study show how existing TPB elements can be modified and expanded to account for the complexities of modern consumer decision-making, primarily online. This study expands the theory of planned behaviour to include privacy concerns, perceived usefulness, and trust, making it more applicable to digital marketing and e-commerce. These additions enhance our understanding of online purchasing behaviour and align TPB with the digital marketplace, where trust, utility, and privacy shape consumer intentions. This research expands TPB to explain consumer behaviour in a digital, privacy-conscious world.

5.3 Practical and policy implications

As e-commerce and digital transactions grow rapidly in Canada, the practical and policy implications are important for managers and industries. Managers should prioritize customer privacy. Privacy concerns significantly affect purchasing behaviour and brand choice, highlighting the need for Canadian companies to improve their privacy policies and communicate them to consumers. Managers should include transparent privacy practices in marketing strategies to build trust and loyalty among data-security-conscious customers. Businesses can gain a competitive edge by using clear, user-friendly privacy notices and complying with Canadian privacy laws like PIPEDA. The positive effect of perceived usefulness on consumer behaviour suggests that Canadian companies should improve their digital platforms' functionality and utility. Managers should prioritize UX and usability to make websites and apps intuitive and meet consumer needs. Businesses can increase online sales by offering features like easy navigation, personalization, and fast transaction processes. User-friendly and efficient online platforms can boost consumer engagement and sales conversion rates for industries entering a competitive Canadian market.

A consistent and reliable online presence is crucial to building and maintaining consumer trust while another key factor influencing consumer behaviour. Canadian companies should invest in trust-building initiatives like third-party certifications, clear return policies, and secure payment methods. Managers should also prioritize customer support by offering multiple channels for fast and reliable assistance. Trust in institutions and businesses drives consumer loyalty in Canada, so building trust is crucial. Canadian businesses can benefit from brand-building initiatives that make customers feel safe and confident in their purchases.

The study recommends that Canadian regulators strengthen privacy protections to maintain consumer trust in digital platforms. Policymakers could update and strengthen PIPEDA to address the growing data collection and use complexity in the digital marketplace. They could also promote transparency and require data audits to protect consumer privacy. Canadian industry associations can work with government agencies to provide guidelines and best practices for companies to manage consumer data responsibly, making online transactions safer. By supporting strong privacy regulations, Canadian policymakers can build a digital economy where businesses and consumers thrive through trust and transparency.

5.4 Limitations and future directions

This study improves understanding of digital marketing consumer behaviour but it has some drawbacks as well. The study uses cross-sectional data, which makes determining causality between privacy concerns, perceived usefulness, trust, purchasing behaviour, and brand choice challenging. Cross-sectional research shows only one time point, making causality difficult to determine (Bhatti & Rehman, 2019). Future research should use longitudinal designs to examine these relationships over time to better understand online consumer behaviour dynamics. Secondly, the geographical sample could have been more extensive, which may limit its applicability to other cultures and regions. Future studies should collect data from diverse populations across multiple regions to improve generalizability because cultural norms and values influence consumer attitudes and behaviours (Hansen et al., 2018). Cross-cultural comparisons would illuminate how different cultures affect privacy concerns, perceived usefulness, and trust in online shopping, expanding theoretical understanding.

Thirdly, self-reported measures are susceptible to social desirability and common method biases (Podsakoff et al., 2003). Self-reported data may inflate correlations between variables, affecting results. Future research should use objective measures or experimental designs to reduce biases and validate findings. Mixed-methods approaches that combine quantitative and qualitative data may also help explain online consumer behaviour. This study focuses on privacy concerns, perceived usefulness, and trust, but many other factors affect online consumer behaviour. Prior research has shown that perceived risk, ease of use, and social influence digital consumer behaviour (Chopdar et al., 2018; Indarsin & Ali, 2017). Future studies should include more variables to create a more complete online consumer behaviour model. Exploring moderating factors like age, gender, and technological proficiency may reveal how the consumer segment views privacy, usefulness, and trust in online shopping.

5.5 Conclusions

Privacy concerns, perceived usefulness, and trust affect online shopping consumer purchasing behaviour and brand choice influences consumer attitudes and behaviour, showing that the interaction of factors influences online purchasing decisions. Privacy concerns positively affected purchasing behaviour and brand choice, suggesting consumers prefer brands that protect their data. The privacy calculus model suggests privacy concerns influence online consumer decisions (Dinev & Hart, 2006). Perceived usefulness was the strongest predictor of purchasing behaviour and brand choice, demonstrating the importance of utility and functionality in consumer engagement. The TAM has shown that perceived usefulness predicts technology adoption (Ventre & Kolbe, 2020). This study shows that perceived usefulness positively affects consumer behaviour, highlighting the need for online platforms to prioritize ease of use and value-added features to attract and retain customers.

Trust was also critical to consumer brand choice and purchasing behaviour. It was found that consumer trust is crucial for online transactions, especially in high-risk environments like e-commerce. Trust lowers risk and increases behavioural control, influencing purchasing decisions. Ponte et al. (2015) and Hansen et al. (2018) also stressed the importance of trust in digital consumer behaviour. The TPB is expanded by adding privacy concerns, perceived usefulness, and trust as consumer behaviour predictors. This research improves the understanding of online consumer decision-making by extending TPB to include these constructs. The results support the idea that attitudes, perceived behavioural control, and trust influence purchasing intentions. This enhanced TPB better explains digital consumer behaviour, where privacy, utility, and trust are essential.

These findings have significant practical and policy implications. The emphasis on privacy, perceived usefulness, and trust suggests that data security, user experience, and trust-building initiatives can improve consumer engagement for managers and businesses. The findings show policymakers that strong privacy protection frameworks are needed to maintain consumer confidence in digital platforms. Strengthening privacy regulations and encouraging transparency will create a trustworthy digital economy where consumers feel safe using online services. This study concludes that privacy concerns, perceived usefulness, and trust influence consumer purchasing behaviour and brand choice. These constructs give the TPB a nuanced view of digital consumer decision-making. Businesses must prioritize privacy, utility, and trust to improve consumer attitudes and online transactions. Addressing these factors can boost consumer engagement, brand loyalty, and business success in the competitive e-commerce world.

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