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Exploring The Role of Behavioural Economics Influencing Consumer Decision Making in an Era of Artificial Intelligence

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Abstract:

This paper explores the role of artificial intelligence and behavioural economics in influencing consumer decision making, and determining psychological techniques utilized by AI through tools like chatbots and virtual assistants which help impact consumer choices. It focuses on how Generation Z is impacted by AI personalization which causes regret aversion, and leads to impulsive buying behaviour. A two phase multi-method design used. A PRISMA-based systematic literature review across ABDC, Web of Science, Scopus and IEEE Xplore-indexed sources in phase 1 to explore how buying intentions are influenced by AI tools. Phase two uses an embedded case study procedure which is used in a qualitative multiple case study design, the cases about AI tools used for retail, influencer marketing were intentionally used. Data triangulation took place through customers' opinions and peer reviewed articles. Customers tend to trust human influencers more because it provides them with social proof. But this gap is decreasing because of AI strengthening its relevance. However consumers worry about algorithmic biases and privacy concerns leading to a decrease in trust and this has an effect on their long term purchasing behaviour. The paper proposes a framework that combines technology adoption models to behavioural economics, providing a theoretical foundation for ethical AI regulation in marketing 5.0. Platform developers, marketers can use a framework that balances customization and ethicality.

Keywords: Behavioural economics; artificial intelligence, consumer decision-making, algorithmic personalisation, Generation Z, Marketing 5.0

1 Introduction

The framework of decision making has been drastically altered because of the rapid spread of artificial intelligence (AI) within consumer platforms. While traditional economics demonstrates that people always make rational logical decisions, behavioural economics contradicts this by showing that consumer decisions rely on cognitive bias and heuristics. A qualitative study was conducted using focus groups, interviews and observational studies. It explored the relationship between AI driven personalization and consumers from Japan and Singapore to explore how culture plays a role in adopting AI tools. The findings show that AI personalization reinforces confirmation bias while dynamic pricing provokes impulsive buying because of loss aversion [1]. Consumers are influenced by biases which gives us a better understanding of consumer behaviour by taking into account real life limitations like cognitive load, time constraints, incomplete knowledge [2]. Hence it is vital to study the implications of behavioural economics, AI and entrepreneurship to make a revised management structure that helps entrepreneurs increase market flexibility and avoid cognitive biases [3].AI provides businesses with an increased level of predictability and allows companies to easily anticipate consumer choices, because AI has the ability to analyse large data sets in real time and observe the decision-making patterns. With the advent of personalized marketing where AI evaluates their personal data and adjusts their recommendations accordingly [2].

Personalization gives the consumers the best experience while improving the business performance however this does raise ethical issues. One of the major concerns is data privacy because AI systems rely on data from consumers without their agreement or understanding of how it is being used [2]. Personalization also comes in with understanding the intricacies of cultural norms. For example, between Japan and Singapore are seen, as Japanese consumers had a trusting and careful outlook on technology whereas in Singapore their mindset was practical and efficiency driven. This highlights the need for ethical guidelines to manage the data privacy issue and consumer manipulation [1]. Another concern is algorithmic biases since AI models receive training on bias data hence they favour some social groups. Looking ahead, accountability, fairness, and openness needs to be present to guide AI systems to not take advantage of the consumers' vulnerability instead to serve consumers interest [2]. The Japanese and Singaporean consumers revealed that AI personalization catered to their needs and that led to higher probability of making the purchase [1].AI tools have the power to metamorphose the functioning of businesses and the predictive power of technology can foster accurate business decisions in an augmented arena. There are multiple external stimuli and emotional underpinnings which have implications on consumer buying behaviour, AI has the power to analyse the behavioural underpinnings and complex psychosocial factors that influence consumer buying behaviour [4]. Businesses may use AI driven techniques to promote sustainable products, and the researchers can use these findings to further investigate how age and gender influence decision making. The academic community can more accurately predict how lifestyle products will change due to the technological influence [5].

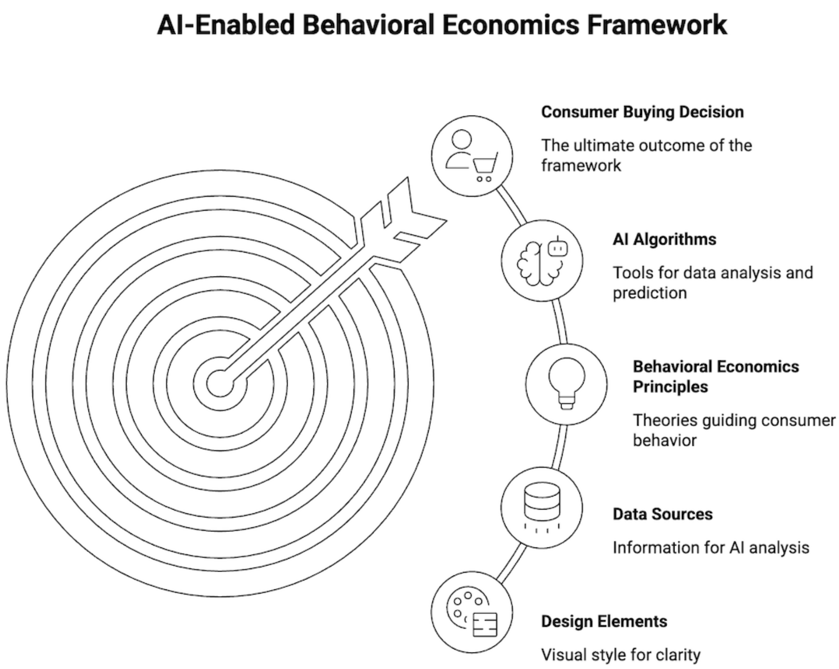

Fig. 1. AI-enabled behavioural economics framework

To understand the complexities of modern buying patterns the author uses stochastic mult objective optimized deep neural networks designed to accurately predict consumer preferences. By processing various datasets this structure offers insights on marketing techniques. The study focuses on a model that has an accuracy rate of over 98% and a comprehensive data pre-processing step, this shows how companies improve customer engagement using AI driven optimization and personalized content [6]. This study shows how automated decision making acts as a link in the purchasing experience by observing the relationship between behavioural economics and technology. The results showed the need for security and privacy concerns are weighted against personalization and emotional engagement [7]. Businesses may use AI driven techniques to promote sustainable products, and the researchers can use these findings to further investigate how age and gender influence decision making. The academic community can more accurately predict how lifestyle products will change due to the technological influence [5]. In conclusion the study provided a foundation for marketers to understand the psychological drives in their consumers. This helps companies develop customer loyalty [7]. These tailored methods are powerful because AI systems can analyse consumers social media activity to find out the consumers preferences and alter the messages accordingly [2].Advanced technology and personalized targeting increases practicality and efficiency for the consumer however the consumers privacy is compromised due to these technologies. A contradiction observed is that, although this helps in removing everyday hassles it may harm consumers wellbeing by lowering individual liberty [8]. According to findings ambiguous numbers work better for products that are meant for pleasure whereas consumers prefer having detailed information when making practical purchases. This is due to a psychological alignment, conceptual fluency which determines how easily the brain processes different types of information [9]. The goal is to find future research possibilities which can be beneficial in finding a balance between technology and the human need for individuality [8]. Research objective this study explores how behavioral economics and machine intelligence influence consumer choice. Focusing on how chatbots and other AI driven platforms use personalization that leads to regret aversion, impulsivity which affects purchasing intention. It evaluates the contrast between the effectiveness of human influencers and AI agents to promote consumer engagement using marketing 5.0 and to analyze the ethical concerns of excessive personalization to guide ethical AI management in consumer centered markets.

The arrangement of the paper is as follows. Section 2 contains a literature review at the crossover of AI and behavioral economics. The research question and hypothesis are included in Section 3. And exploring RQ1 by a PRISMA based examination, and RQ2 by qualitative case studies, while also defining the research methodology is all addressed in Section 3. Section 4 explores the results and discussion. Section 5 addresses the conclusion of the paper and future study objectives are presented.

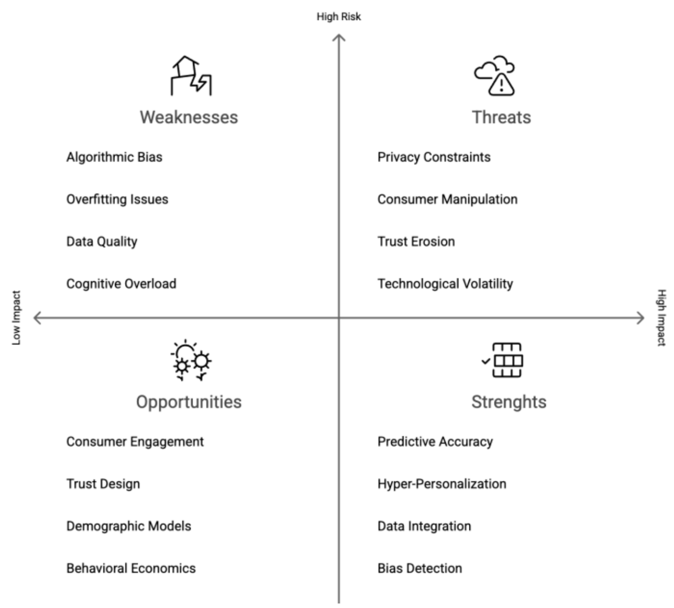

Fig. 2. Artificial intelligence integration in behavioural consumer analytics

2 Literature review

Consumer behaviour has been changed due to generative technologies which have drawbacks and opportunities for businesses. However the academic community still lacks a thorough analysis that would give the current state of research and suggest a direction for the future. To address this knowledge gap a hybrid systematic literature review and bibliometric analysis are carried out to predict patterns. A Theory Context Characteristics Methodology (TCCM) analysis framework is used alongside this hybrid study. This provides an in depth plan for further research exploring the relationship between behavioural economics and automatic systems. The goal is to provide researchers with the ability to understand the relationship between human choices and technology [10]. By applying its ability to analyse large data sets, and patterns AI has the potential to change the brand consumer dynamics. Businesses may understand their consumers' needs better due to the data driven insights and chatbots and virtual assistance are examples of AI innovations that have improved customer service by personalization. Furthermore, a conceptual model was proposed that supports the impact of AI on consumer behaviour in three areas satisfying consumer needs, influence among industries, and improving customer experience with AI driven products [11].

A systematic literature review outlines present academic knowledge about how social media and generative AI is affecting consumer choice. The results show that even though generative AI increases consumer engagement at the same time, it raises ethical concerns like algorithmic bias and privacy issues. It also examines how suggestion engines and chatbots can act as threats or an asset [12]. A survey conducted on 300 people revealed that impulsive traits and social evidence are the main reason for rapid buying behaviour. Consumer intention is also impacted by other variables like anchoring, and fear of a possible loss. To measure how these biases affect the probability and speed the researcher used a multi attribute behavioural economics model, the findings offered firms ethical guidelines and strategic insights hence it is useful for both security and profit. These results tell us how important it is to include measurement of behaviours while predicting economic outcomes [13].While studies pay more attention to observable human behaviour it is also important to take into account implicit biases that indirectly influence consumer choices. Hidden factors like regulatory focus and regret aversion can impact more observable behaviours and how customers evaluate the available choices [14]. Firms use consumers' personal data often, without the consumers being aware about it. This is done to examine consumers' online activity to develop predictive tools that impact consumer choices. Generation Z is the main target audience for these tactics because they heavily rely on social media to make buying decisions [15].

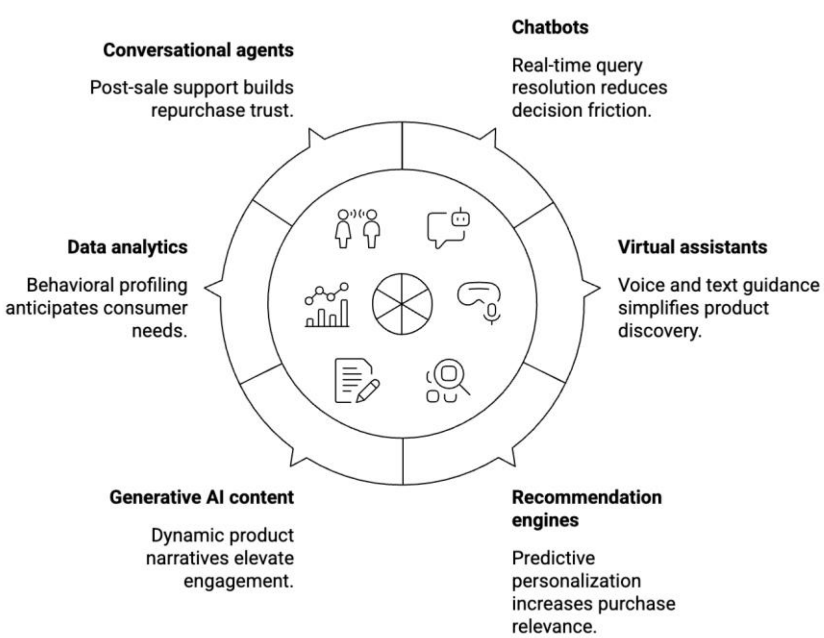

Fig. 3. AI-driven consumer purchase intention

AI and other digital tools use natural language processing to personalise recommendations and evaluate large quantities of data. Consumers are moving past conventional marketing and towards algorithmic guidance due to AI's honesty and neutrality, as it is viewed as a resource that doesn't have extraneous motives, contradicting human driven marketing strategies. However, it is crucial to recognize the drawbacks of AI. Although AI is exceptional at providing recommendations based on individual algorithms, human influencers have an emotional connect with their audience, and consumer decisions are based on interpersonal trust, ultimately in a digitised world human endorsement is still an important part of decision making. By simplifying complex information AI significantly impacts consumer decision making. As it removes the need for people to interpret contradicting reviews and advertisements, hence reducing the cognitive load for the consumers and making it a more tailored and customised experience. This increases user pleasure, as it is seen that customers make quicker and accurate decisions and purchases using AI.AI assisted purchasing creates a psychological relationship between personal agency and user confidence. It argues that when automated systems help users make decisions they are more likely to adapt to it. Personalized interaction and organization credibility are factors that cause consumers to rely on computerized recommendation [16].

According to the Technology Acceptance Model, it was found that research of 327 customers. We have seen a shift in the marketing industry due to AI agents as they provide predictivity to the firms and are influenced by human impulses, furthermore they are comparatively less expensive however, research on how AI agents compare to human models in terms of purchasing intention is still needed. Digital influencers provide firms with a risk-free choice as they don't cause controversies or get caught up in personal issues. They also significantly increase consumer trust and familiarity which leads to an increase in the chances of consumers making a purchase [17]. The current research uses the "black box" model which predicts what consumers will do but doesn't explain why and they are designed for a specific type of AI so it can't be generalized. This research proposes a computational framework which can evaluate various kinds of AI assistance [18]. Research shows that human influencers are still more capable of maintaining a long-lasting image needed for brand loyalty, however AI influencers have the ability to attract consumers who are searching for originality and slowly consumers have started accepting recommendations but there is still a lack of connection which is deeper with human influencers [19].

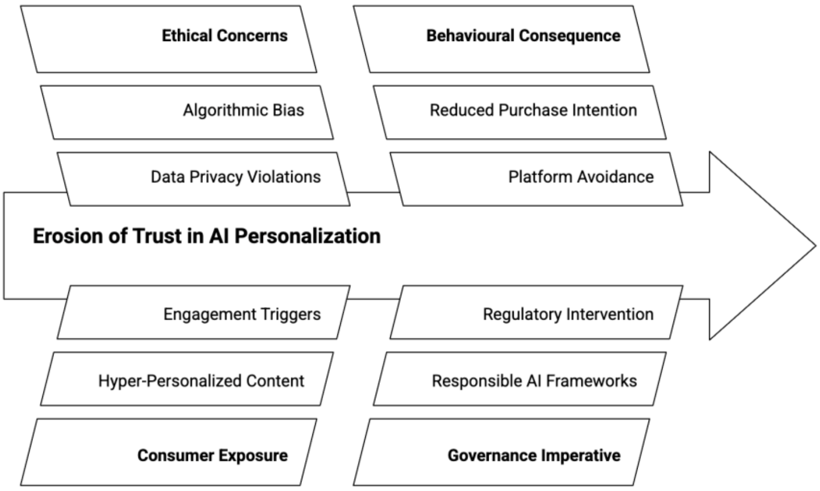

Fig. 4. Analysing the erosion of trust in AI personalization

There are 3 dimensions of AI productsinteractivity, multi-functionality, and AI intelligence. They are categorized to analyse their effect on privacy, individuals freedom, and social wellbeing. There are growing concerns regarding AI like potential unemployment and biases. To address these concerns firms should practice corporate social responsibility which offer ethical designs. The institutional environment and the stakeholder theory can also lead to enhancing the ethics of artificial intelligence [20].There are 6 ethical frameworks like virtue ethics, utilitarianism, ethics of care, these frame how different consumers justify their purchases. It is important to keep AI based advertisements ethical this can be done by making sure they are in line with the stakeholders desires and moral standards [21].

Table 1. Extensive literature review for behavioural economics influencing consumer decision making

References	Key Findings	Research Gap	Limitations
International Journal of Management, Business, and Economics.	Biases have a huge impact on consumer decision making	The impact of AI on cognitive bias processes	Depends on secondary literature review
Foxall, G. R. (2017). Behavioural economics in Consumer Behaviour Analysis.	Combines fundamental concepts from marketing research, psychology, and economics	Inadequate descriptive models of real-world buying patterns	The depth of actual proof is limited by journalistic style

Yamamoto, Y. H. (2024d).	AI personalization promotes preexisting cognitive biases	Not enough studies of Asian customer markets	High numerical generalizability is limited by the qualitative method
Liu & Han (2020)	Search satisfaction is greatly impacted by reference points.	Practicing user-side features such as mental bias	Studies restricted to task-based search databases
Aoujil et al. (2023)	Rapid increase in AI behavioural research	Limited research in behavioural macroeconomics fields.	Information limited to Web of Science
(Frederiks et al., 2014)	Biases drive decisions, not rational choice	Missing unified behavioural economics theoretical framework	Contextual variability hinders research results' generalisability
(Korteling et al., 2023)	Biases stem from ancient evolutionary heritage	Biases ignored in various political domains	Education rarely corrects ingrained cognitive distortions

3 Research methodology

This research has a multi research design with a two phase approach for RQ1 a systematic literature review is conducted based on PRISMA from IEEE Xplore, Scopus, Web of Sciences using Boolean search strings containing terms like "AI chatbot", "consumer purchase intention". For RQ2 and RQ3 qualitative case studies are used focusing on social commerce, AI-driven retail. Through peer reviews data triangulation is achieved allowing for a comprehensive analysis of concepts like consumer trust, algorithmic bias perception, and impulsive buying. The two phases combined offer a balance of conceptual depth and theoretical rigor suitable for the scope of the study.

3.1 Research design

This study uses numerical and qualitative data because it is difficult to measure because human behaviour is complex and hence a mixed method research design is used to gain deeper insights. This integrates a PRISMA systematic literature review with a thematic synthesis of the studies included; this was used to gain a broader understanding on research about AI and consumer behaviour and to also gain a deeper understanding on how psychological factors influence purchasing decisions. It adopts a post positivist epistemological stance because even though objective truth exists, previous studies shape our understanding of it. This makes it perfect for a study that examines existing evidence on AI's role in consumers decision making and doesn't just rely on proof from a single experiment.

3.2 PRISMA systematic literature review

The primary methodological architecture for this study is the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework. This was used because the paper combines different areas of knowledge ranging from AI ethics to consumer psychology, digital marketing, and behavioural economics and it requires clear structure, repeatable process which is provided through PRISMA. This makes the review transparent and reduces researcher bias making it more reliable. A search was conducted across 5 academic databases from 2019 to 2025. 2019 was selected because AI conversationists and recommenders started being commonly used in 2019.

3.3 Thematic synthesis

To recognize, evaluate and interpret patterns a thematic synthesis was conducted after the PRISMA process. A thematic synthesis combines different studies and identifies patterns and develops new insights. There were 3 stages following the Thomas and Harden (2008) framework (1) line by line coding using Taguette open-source software for each study, (2) grouping codes into categories to develop themes, (3) development of analytical themes that address the hypotheses and the research question. This builds 4 analytical themes with each theme corresponding to one or more of the hypotheses.

3.4 Conceptual framework

The conceptual framework followed by this study includes 4 theoretical models interpret and evaluate the thematic synthesis findings, and hypothesis.

3.5 Research questions

RQ1How do AI-powered devices affect consumers' intentions to make purchases?

RQ2How does Generation Z's tendency for impulsive purchases come from social evidence integrated into AI-mediated material, and do human influencers make purchase intentions more effectively than AI agents?

RQ3Do consumer worries about security and algorithmic bias in AI customization have a negative impact on long-term purchasing behavior and trust?

3.6 Hypotheses

H1. Does AI's personalisation tool have a positive effect on consumers buying decision.

H2. Social evidence in AI-mediated material predicts Generation Z's impulsive purchasing tendency, human influencers generating higher buying intention than AI agents.

H3. Higher consumer perception of algorithmic bias and privacy risk negatively moderates the relationship between AI personalisation and consumer trust, reducing long-term purchase intention. The relationship between AI customization and consumer trust is negatively influenced by concerns about algorithmic bias and security lowering long term purchase intention.

3.7 Case study: AI-mediated social proof and impulsive buying among Generation Z

RQ2. How does Generation Z's tendency for impulsive purchases come from social evidence integrated into AI-mediated material, and do human influencers make purchase intentions more effectively than AI agents?

This case study explores how Generation Z's tendency for impulsive purchases come from social evidence integrated into AI-mediated material and if AI agents are at a disadvantage compared to human influencers in developing purchase intention. This case study is in line with Yin's (2018) integrated case study methodology, the case is built by combining empirical research, platform-level information, and business insights from social commerce ecosystems.

3.7.1 Context and rationale

Generation Z are the first digitally native generation because they grew up with the algorithmic online environment and their purchasing behaviour has highly been affected by peer validated content, customized suggestions, and social media exposure. Hence this generation has become the primary subject for investigating the behavioural effects of AI-generated social proof because AI customization has become a part of daily buying experience [22]. Instagram and TikTok Shop foster an environment that leads to unplanned, quick purchases through socially validated content, time limited purchase signals, and tailored recommendations [23].

3.7.2 AI-mediated social proof and impulsive buying

Social commerce consumers' propensity to make impulsive purchases is positively impacted by AI's content features according to empirical data. Credibility ($\beta = 0.341$, $p < 0.001$), attractiveness ($\beta = 0.178$, $p = 0.003$), novelty ($\beta = 0.141$, $p = 0.019$), and trust ($\beta = 0.125$, $p = 0.025$) were found to be major determinants of impulsive purchasing behaviour in a study with 266 Indonesian social commerce consumers (Fadilah et al., 2025). The biggest indirect effect was found for trust, highlighting the fact that social proof methods incorporated into AI-generated advertising content work best when users believe the content to be authentic and engaging rather than algorithmically generated. Platform specific data from Shopee further supports this, showing that Generation Z consumers are more prone to quick purchases motivated by product features, sales bonuses, and socially reinforced content [24]. Structural equation modelling (SEM) results validate the causal link from AI triggers to impulse-driven buying response. Research using the Stimulus-Organism-Response (SOR) framework shows that AI system features, specifically accuracy, interaction, and behavioural findings, directly trigger rash purchases among Generation Z [25]. Overall, these results demonstrate that algorithmic social proof serves as a strong behavioural incentive for this consumer group when it is presented through engaging and customized AI interfaces.

3.7.3 Human influencers versus AI agents: purchase intention

A crucial moderating feature is provided by the comparative question of whether human influencers generate intent to purchase more effectively than AI agents. Even though AI agents are adaptable and accurate they have not mastered emotional authenticity, and parasocial interactions which are human influencers' persuasive power. With its engaging and immersive product experiences that greatly increase user engagement and intent to buy above static text or image formats, video content in particular has become the predominant medium through which both human and AI-generated social proof is shown to Generation Z audiences. But the data also shows that AI-generated media in promotional video and live-streaming modes is quickly bridging the credibility gap. Especially among younger consumers who tend to be less resistant to AI-mediated persuasive techniques, AI content that is created with high engagement and reliable signals results in behavioural outcomes that are similar to those of human influencer-based campaigns [23]. The clear credibility and social proof embedded in the data itself are the essential distinguishing features, not the source.

3.7.4 Implications

Through a combination of customization, algorithmic reliability, and interactions this case study shows that social evidence is incorporated in AI content and is a powerful and proven source of impulsive purchases among Generation Z. Even if human influencers have an advantage of emotionally connecting with the customers, AI is still successful at providing social evidence leading to quick purchases. These results directly answer the RQ2 and are a concrete base for a theory that argues behavioural economics is enhanced by AI marketing frameworks.

A research study by Lina et al. proposes that advertisements and social media affect how Generation Z behaves on Shopee because it shapes their impulsive buying tendencies. Moreover, video content is a better engagement tool when compared to still media as it improves the product presentation increasing consumer engagement. However, research on emotional factors that affect quick purchases is still insufficient even after significant advances in research for understanding online shopping behaviour. Previous research lacks in exploring the real impulsive buying habits or the psychological impact these videos create, instead it majorly focuses on the temptation to make these rash purchases. This research intends to address these gaps by analysing how product presentation videos impact Generation Z's impulsive online purchasing habits, with a primary focus on the Shopee video platform. The main objective is to analyse the complex relationships between stimuli in online settings and how they influence impulsive purchases. To improve consumer behaviors models and incorporate digital stimuli into impulse buying frameworks, this research aims to identify the mechanisms driving impulsive buying in digital environments. The study specifically looks at how customers' pleasure is affected by external variables such as quantity pressure, time pressure, economic incentives, visual and auditory features, and social impact. By examining these dynamics, the study aims to comprehend how external factors influence emotional reactions, which in turn influence impulsive online buying decisions [24].

AI is known as one of the strongest drivers, particularly for Generation Z. The study calculates the parameters of the triggered purchases shown by Generation Z which is assessed using the Stimulus-Organism-Response model. The results of the SEM model demonstrate that Gen Z's impulsive purchasing behaviour is directly impacted by accuracy, engagement, and observations [25].

3.8 Case study: algorithmic bias, privacy concerns, and the erosion of consumer trust in AI personalisation

RQ3. Do consumer worries about security and algorithmic bias in AI customization have a negative impact on long-term purchasing behaviour and trust?

This case study examines if trust and long-term purchasing behaviour are adversely affected by consumer worries about biases in algorithms and data security in AI-powered customization. This case uses Yin's (2018) case study methodology, relying on empirical research, and data triangulation is achieved amongst peer reviewed sources.

3.8.1 Context and rationale

Due to AI algorithms the relationship between the business and audience has changed. They can now increase consumer engagement by providing the customers with a personalized shopping experience [26]. But there is a transparency gap because these systems that provide personal information are hidden from the public eye and this creates anxiety in users and lack of trust [26]. From a behavioural economics point of view, there is lack of disclosure because consumer decision is influenced by cognitive biases rather than rationality [27]. When consumers fear that AI is taking advantage of these biases through nudges, anchoring this undermines the consumers feeling of liberty.

3.8.2 Algorithmic bias and privacy as trust determinants

Even though personalization leads to higher engagement, the moral integrity of the data methods restricts its effectiveness. Research shows that privacy concerns lead to decrease in loyalty and consumer trust [28]. As a result, the advantages of AI-mediated personalization are uncertain, requiring strong governance to fix the lack of trust present in hidden systems. By creating systemic differences in pricing and recommendation outputs [27], algorithmic bias from skewed datasets worsens the lack of confidence. According to behavioural economics, these unfair violations set off a scepticism heuristic, which causes users to not trust all upcoming platforms. This cognitive change essentially increases the long-term behavioural effects of a single unfavourable encounter by turning isolated impressions of injustice into lasting barriers to involvement.

3.8.3 Long-term buying behaviour consequences

The advantages of hyper customization are offset by platform avoidance because of lack of trust due to the perceived intrusive behaviour [26]. Long-term effects of this lack of trust include systemic expenses, lower customer lifetime value, and harm to reputation. Incorporating ethical governance is required to address these behavioural implications and guarantee the long-term viability of AI-mediated user engagement [28]. Generation Z has a dual mindset where they are aware about the data rights and manipulation however they are open to AI driven shopping. This shows that customer engagement is conditional and requires ethical data management for it to be sustainable [29].

3.8.4 Implications

This study focuses on how consumer trust and buying patterns that depend on responsible AI management have an impact on the business's performance. There is a clear causal relationship, since they aren't transparent about the data customers get anxious about their privacy which leads to decrease in trust and loyalty. These results address RQ3 and support the argument that ethical AI methods are a financial requirement not just a moral decision [25].

To go beyond the idea that consumerism is rational, modern businesses have started combining data science and behavioural economics. Businesses can systematically discover cognitive biases and emotional triggers that influence everyday buying habits by using AI. Highly customized marketing and the use of dynamic pricing techniques are possible by this connection. This also greatly increases profit margins and retains customers. Businesses can predict requirements through predictive models, however there are ethical concerns. This collaboration converts consumer data into strategic information which gives them an advantage in the market which is moving towards automation [28]. Behavioral economics contradicts traditional economics, it tells us how biases and emotions influence consumer decision making. And AI uses datasets to determine these heuristics which allows businesses to make a hyper customized marketing technique that recognizes the consumers emotion state and leads to accurate predictions. However, there are ethical concerns about privacy and algorithmic biases taking advantage of humans' vulnerability. For AI to work in favor of the consumer's wellbeing, transparency and ethicality is needed [29].

3.9 Theoretical underpinning

Behavioural models, data, and consumer choices on online platforms are important factors of the modern insurance concept, however there is limited research combining the consumer decision-making model, behavioural economics, and information system theories focusing on insurance-related purchasing and computerised decision-making processes. Information system theories explore why consumers prefer digital insurance. The mentioned factors affect the consumers decision making about using online insurance platforms, such as performance and effort expectancy, do people recommend it, and if they have the technical requirements [30].

Table 2. Summary of case study findings by research question

RQ	Case Study	Theoretical Underpinning	Key Findings
RQ1How do AI-powered devices affect consumers' intentions to make purchases?		Effort expectancy, the simple one tap purchases and the utility of AI recommendations drive the customers to make impulsive purchases especially after seeing social proof.	Human influencers, reviews and other social proof are an important factor that affect consumers' trust and their purchases; however, even AI simple recommendations impact consumer choice.
RQ2How does Generation Z's tendency for impulsive purchases come from social evidence integrated into AI-mediated material, and do human influencers make purchase intentions more effectively than AI agents?	AI-Mediated Social Proof and Impulsive Buying Among Generation Z	Consumers emotions along with social influence have an effect on the drive that leads to impulsive buying behaviour. It is also increased by useful AI recommendations.	Human influencers are more efficient than AI at building impulsive purchase intentions in consumers.
RQ3Do consumer worries about security and algorithmic bias in AI customization have a negative impact on long-term purchasing behavior and trust?	Algorithmic Bias, Privacy Concerns, and the Erosion of Consumer Trust in AI Personalisation	Consumers trust on AI depends on that platform's ethical practices and the consumer's risk perception. The ease and simplicity of AI platforms doesn't have an effective impact on their impulsive purchasing behaviour if the consumers feel there are privacy risks.	Consumer trust on AI personalization decreases when they think that it's unethical and their privacy is being violated. These worries are amplified by weak data control which will result in decrease in trust and lead to losing consumers in the long run.

4 Results and discussion

This study is supported by previous studies. A study has found that there has been significant growth in the interest in the use of AI in behavioural economics and consumer choices. AI tools like machine learning, chatbots, and recommenders were useful predictors of consumer choices and helped increase engagement. It also explores how even though AI has helped increase consumer engagement and impulsive purchases through personalization there are ethical concerns regarding privacy and algorithmic biases which should be regulated in order for AI to be more incorporated into behavioural economics [31]. AI driven customization and pricing techniques come together to take advantage of cognitive biases like confirmation bias and loss aversion, and cognitive load is decreased due to IoT devices. This makes decision making easier and helps facilitate the process by using recommenders. It also highlights the cultural difference in technology as Japan had a more trust-based approach and Singapore focused more on efficiency and ease of use, it concluded that customers would only interact with AI driven customization if the company would be open about how their data is collected [32].

Our findings combining the two case studies, this study had 4 theoretical propositions P1–P4. P1social influence integrated into AI generated content is positively correlated to impulsive buying habits in Gen Z. P2human influencers maintain an emotional connection with the customers which leads to customers trusting human influencers more than AI agents, but this advantage is minimized when customers find AI easier. P3algorithmic biases and privacy concerns decrease the trust consumers have in AI driven personalization. P4no transparency in data governance discourages repurchase behaviors in consumers. The novelty of this study is that it connects both behavioural economics frameworks with information-systems technology-acceptance. Previous works treat social proof and privacy as two completely different research paths, one based on parasocial theory and the other based on algorithmic responsibilities. Aligning with recent research, this synthesis reinforces that concerns about privacy and algorithmic concerns aren't just small factors that affect consumer engagement with AI but it is one of the biggest reasons that affect whether customers trust AI or not. The policy conclusion is that both reduction in the impulsivity design and increasing consumer trust should be implemented. This refers to policies that promote transparency and protection of data while helping consumers make well thought out decisions. This used a 5.0 marketing framework that supports the 4-pillar framework.

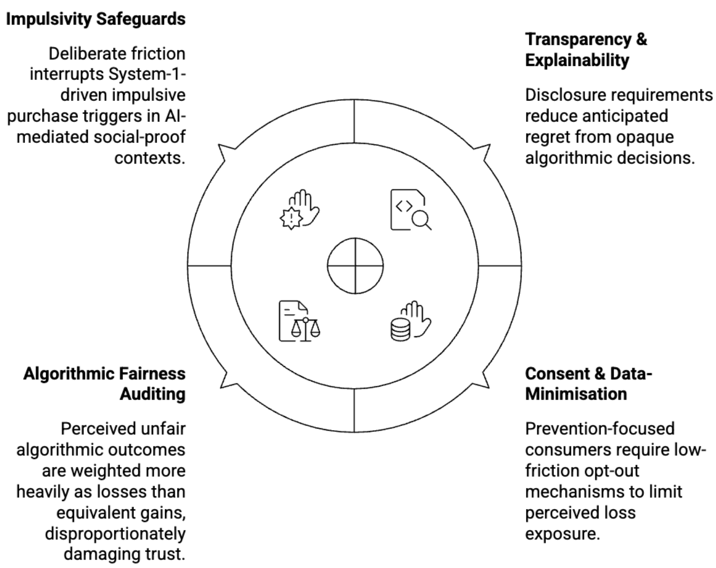

Fig. 5. Four-pillar ethical AI governance framework

4.1 Ethical considerations

No human participants were involved since this study analysed secondary published literature, this removed the need for individual consent.All papers included are cited in full IEEE format, content is not paraphrased without credit. Any use of AI tools in editing is disclosed in the author contributions statement as per IEEE publication ethics guidelines. The study recognizes that it is biassed towards the western population and does not equally represent all cultures making it harder to generalize to a larger population.

4.2 Limitations

This research relies on secondary data, so conclusions are based on existing data and this study focuses on Gen Z so it's difficult to generalize it to all age groups. The PRISMA review is restricted to papers written in English so significant research papers in Korean, Chinese or Arabic are excluded. Primary data isn't being used which restricts the capacity to test the hypothesis using empirical evidence.

4.3 Future scope

Future research should use quantitative methods like structural equation modelling and explore the theory from different cultures to find out if it's applicable worldwide or to certain regions. And conduct experiments to compare AI agents to human influencers to find out if there is a causal impact and it's not just an association.

5 Conclusion

This study is centred around 3 research questions that explore how AI and behavioural economics are combined to influence consumer decision making. The three research questions examine AI based social evidence, how AI tools impact purchase intentions, privacy concerns, and Gen Z's impulsive buying habits. Both the multiple case studies and the PRISMA based systematic review findings were the same, that AI personalization has both a negative and positive effect on consumer behaviour. It helps increase engagement and reduces customers' cognitive load through parasocial trust, social evidence, recommenders however this also raises privacy concerns about the opaqueness about how they collect their data which decrease the customers' trust. The study's theoretical framework is a novel integrative framework that combines behavioural economics like regret aversion to technology acceptance models that include performance and effort expectancy. This shows that the cause for impulsive buying and decrease in consumer trust is caused by the same AI system. Companies shouldn't consider AI governance and impulsive buying as two separate problems instead they should be included in one strategy that includes transparency, safeguards against impulsive purchasing because if businesses only focus on one of these the consumers will still lose trust. Future quantitative cross-cultural studies will increase the generalizability. This will help turn this study's findings into official regulations for companies using AI in markets.

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