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Artificial Intelligence-Driven Digital Influence and Its Impact on Junk Food Consumption Among Youth

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Abstract

This study examines the influence of Artificial Intelligence applications and AI-driven marketing activities on junk food purchase intention among youth. The research design embraced in the study is quantitative research based on a structured questionnaire, which is measured on a five-point Likert scale. Constructs used in the conceptual framework combine those of the Technology Acceptance Model, Theory of Planned Behaviour, and Social Cognitive Theory. Among the key variables, one will find exposure and AI knowledge, AI-driven socialization and food marketing power, apparent usefulness, apparent ease of use, and intention to purchase junk foods. Structural Equation Modelling (SEM) will be used as the method of data analysis to test the hypotheses and investigate the mediating relationships based on the data that the researchers received from the youth respondents. The study found that digital influence could not be simply a question of technological exposure, but a complex psychological process that is guided by Perceived Usefulness (PU). The results also show that, although the youth are extremely exposed to marketing based on AI, the exposure does not directly translate into purchase intentions. Instead, it has to be filtered on a perception of utility first. The results present information to policymakers, medical practitioners, and marketers in terms of the ethical implications of AI-based marketing to influence the dietary patterns of the youth.

Key Words: Artificial Intelligence, Junk Food Consumption, Technology Acceptance Model, Purchase Intention.

1. Introduction

The main risk factor for obesity and other non-communicable diseases is eating poorly. A huge shift in nutrition is taking place, characterised by quickly evolving dietary patterns. Traditional diets, which were high in fibre and primarily made up of whole foods, are giving way to more western-style diets, which are processed and high in calories. Rapid economic development, urbanisation, and an increase in the use of packaged and processed foods, also referred to as "junk foods" have all coincided with this shift. These foods have less nutrients and vitamins and characterised as HFSS (High in Fat Sugar and Salt). Scientific evidence shows junk food has been medically found to weaken body's defence against infection, increased blood pressure, causes weight gain and also contribute to increased risk of cancer (Aiolfi, 2023). Increased consumption of junk food is a major public health hazard that is more common among teenagers and young adults than any other age group, with a global prevalence of over 70% (Potvin et al., 2024). Pelletier et al. (2014) found that descriptive social norms have been linked to a number of weight-related health behaviours, such as eating fast food or junk food among adults and adolescents. Youth are more interested to varieties of food since in that age their body is willing to intake more quantity of food. This vulnerability is being exploited by many food companies to market their food brands and products. As their purchasing power continues to grow, their behaviours, preferences and values will increasingly dictate the evolution of the retail landscape worldwide (Bunea et al., 2024). With the rapid development of Information Technology, and the popularisation of marketing applications, marketing has developed from one-way marketing to interactive marketing, then to precision marketing based on big data and the smart marketing stage supported by AI technology (Yin & Qiu, 2021). AI helps the sellers to predict the customers buying preferences and offer the customised products or services. AI tools like chatbots and personalised shopping assistants enhance convenience and customisation, making the shopping experience easier and more efficient (Bunea et al., 2024). Amid rapid advancements in AI, however, the influence on purchase intention of junk foods, particularly underlying mechanisms, remains unexplained.

The rapid advancement of Artificial Intelligence [AI] technologies has significantly transformed marketing strategies in the food industry, particularly in targeting consumer behaviour. In the context of junk food consumption, AI-powered tools such as personalized recommendations, chatbots, and targeted

advertisements are increasingly influencing consumer choices. Despite the growing integration of AI in digital marketing, there is limited empirical research examining how these technologies affect consumers' purchase intentions, especially in relation to unhealthy food products like junk food. Online shopping has emerged as a popular alternative for making purchases of goods and services with the growth of the internet (Nagy & Hajdú, 2021). The TAM theory provides a robust framework for analyzing how consumers interact with AI-driven marketing tools. However, the application of TAM in the context of AI influencing junk food purchase intention remains underexplored.

This study attempts to examine the influence of Artificial Intelligence (AI) applications and AI-driven marketing activities, along with perceived usefulness and perceived ease of use, on junk food purchase intention among youth applying the theory of the Technology Acceptance Model (TAM). The structural equation model (SEM) is used to analyse the influence and connections between the variables, namely Level of Exposure/ Knowledge to AI, Socialization Effect/ Food Marketing (SEFM), Perceived Ease of Use (PEU), Perceived Usefulness (PU) and Purchase Intention.

The rest of the paper is organised as follows: Section 2 provides the theoretical background of the study; Section 3 presents the literature review and hypothesis development. Section 4 explains the research methodology, followed by results analysis and discussion in Section 5. Finally, the conclusion, policy implications, limitations and scope of further studies.

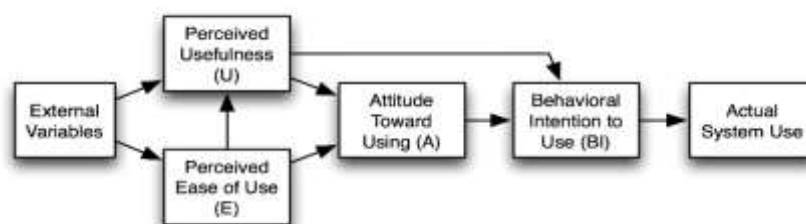
2. Theory background

In alignment with various established theories, this study tries to reveal the role of AI on the junk food consumption behaviour of youth. The study is mainly based on three main theories, such as the Theory of Learned Behaviour, the Social Cognitive Theory and the Theory of TAM. The Theory of Planned Behaviour explains how individuals' different forms of intentions lead to specific behaviours. According to TPB, a person's intention to engage in a behavior is influenced by three key factors: attitude, subjective norms, and perceived behavioral control. In the context of consumer behaviour such as junk food purchases, TPB helps explain how a person's attitudes toward junk food, perceived social acceptance of eating it, and their perceived control over resisting it, all contribute to their likelihood of making a purchase. This theory is particularly relevant in studies involving AI, where intelligent systems may subtly shape these three components through targeted messaging, social cues, and convenience-enhancing features, thereby influencing both consumer intentions and behaviors.

The Social Cognitive theory is a general theory emphasising learning from environment. This framework is well-suited for analyzing how AI-driven technologies influence youth behavior, particularly in areas like dietary habits. AI technologies interact with consumers by designing AI-driven interventions, reinforcing real-time decision-making and targeted promotions. For an instance, a teen who engages with fast-food content is more likely to receive targeted promotions or ads for those products and always need content based suggestions for further purchases.

The TAM, developed by Fred Davis (1986), is a theoretical framework widely used to explain and predict how individuals adopt and use new technologies (Nagy & Hajdú, 2021). Grounded in the Theory of Reasoned Action (TRA), TAM provides a structured approach for understanding users' behavioral intentions based on their perceptions of technology. The basic drivers of acceptance and utilisation of technology is perceived usefulness and perceived ease-of-use. In the context of this study, TAM is particularly relevant in exploring how youth interact with AI-based systems such as recommendation algorithms, food tracking apps, smart ordering platforms, or AI-driven health nudges. Generation Z may have higher expectations for how AI can optimise and streamline their online buying activities due to their comfort level with technology. This study investigates how Gen Z's adoption of AI in online food purchases is influenced by these particular expectations, offering fresh insights into the TAM's application in this specific demographic (Nagy & Hajdú, 2021). By applying TAM, this study aims to assess how junk food consumers perceive the value and usability of AI in influencing their eating behaviors.

Figure 2.1: TAM model



Source: Adapted from Davis et al., 1989.

3. Review of Literature and Hypotheses Development

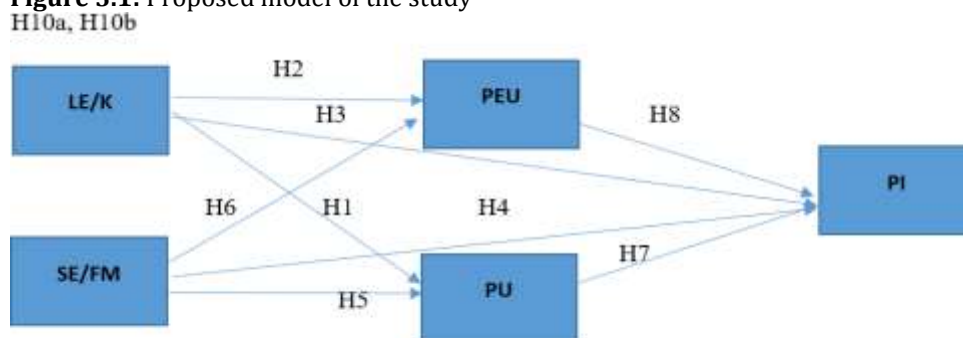
Yin & Qiu (2021), Recent research employing the Stimulus-Organism-Response (SOR) framework demonstrates that AI marketing technology significantly drives consumer purchase intentions by acting as an environmental stimulus. These AI experiences function by enhancing a consumer's perceived utility and hedonic values, acting as a more potent driver of the intent to buy than practical utilitarian benefits. Specifically, the literature has not yet addressed whether the superior ability of AI to trigger hedonic pleasure and curiosity disproportionately leads younger demographics toward impulsive and unhealthy dietary choices. Bunea et al. (2024), Utilizing an adapted Technology Acceptance Model (TAM), research demonstrates that a user's level of AI exposure enhances their perceived usefulness and ease-of-use of these tools, which collectively drive their intent to buy. While AI-driven personalization and "chatbots" are now central to the Gen Z retail experience, food products currently account for a smaller portion (21%) of their AI-facilitated shopping compared to beauty or technology.

In a study examining popular social media influencers on YouTube, Instagram, and TikTok, Potvin Kent et al. (2024) found that marketing efforts often leverage techniques that appeal to youth, such as viral marketing, "fun/cool" themes, and the perceived authenticity of influencers, who are often viewed by children as more relatable than traditional media figures. Because digital platforms use sophisticated methods to maximize engagement, such frequent exposure to unhealthy food cues is a significant concern, as it has been shown to directly influence dietary preferences and increase the risk of obesity among vulnerable young populations. Schepman & Rodway (2020), validated the General Attitudes towards Artificial Intelligence Scale (GAAIS), which differentiates between positive perceptions of AI utility and negative, emotionally-driven dystopian concerns. Their findings highlight a clear divide in public comfort, where AI is welcomed for "big data" automation but viewed with scepticism in domains requiring human judgment, empathy, or social understanding. This distinction is critical for understanding AI's role in health-related contexts, as participants rated AI as significantly less capable and more uncomfortable in roles traditionally involving personal guidance or medical advice.

Nagy & Hajdú (2021), Yin & Qiu (2021), Manna et al. (2023) and Jayasingh et al. (2025), in multi-cultural economies like India, trust is identified as a critical mediating variable that bridges social and functional features to consumer acceptance. Recent studies compare the effectiveness of AI-driven virtual influencers against human influencers. While humans still lead in perceived authenticity and emotional appeal, AI influencers excel in novelty, aesthetics, and precision-driven content personalization, specifically within technology and luxury branding. Due to the limitations of the existing studies, there is a lack of quantitative research evaluating AI technology specifically as a stimulus to extend the boundaries of the traditional Technology Acceptance Model. Existing literature lacks exploration of consumer acceptance and trust at a pan-Indian level, particularly including Tier-2 and Tier-3 cities. There is a limited amount of qualitative research that informs the specific emotions and cultural factors that drive the acceptance of AI personas. Current AI customer service (chatbots) often fails to meet the needs of highly educated groups for personalized and emotional communication, representing a gap in complex semantic interaction.

The proposed Model for analysing the connections between Level of Exposure/ Knowledge to AI, Socialization Effect/ Food Marketing (SEFM), Perceived Ease of Use (PEU), Perceived Usefulness (PU) and Purchase Intention is shown in figure 3.1.

Figure 3.1: Proposed model of the study



H9a, H9b

Source: Compiled by the authors

Based on the review of literature and proposed model, the study developed the following hypothesis:

H₁: The level of exposure and Knowledge to AI has a positive and significant influence on perceived usefulness of AI in the context of AI-powered online junk food purchase.

H₂: The level of exposure and Knowledge to AI has a positive and significant effect on youth's perceived ease of use of AI in relation to online junk food purchases driven by AI.

H₃: The level of exposure and knowledge to AI has significant and positive effect on youth's purchase intentions in relation to online junk food purchases driven by AI.

H₄: The socialisation effect and food marketing of AI has a positive and significant influence on youth's purchase intentions in relation to online junk food purchases driven by AI.

H₅: The socialisation effect and food marketing of AI has a positive and significant influence on their perceived usefulness of AI in relation to online junk food purchases driven by AI.

H₆: The socialisation effect and food marketing of AI is expected to positively impact their perceived ease-of-use of AI in the context of AI-powered online junk food purchase.

H₇: The perceived usefulness of AI has a positive and significant impact on the purchase intentions of youth in the context of buying junk food online using AI.

H₈: The perceived ease of use of AI has a positive impact on the purchase intentions of youth in the context of AI-powered online junk food purchases.

H₉: The relationships between the [a] level of exposure or knowledge of AI and [b] the level of socialisation effect or food marketing of AI, and the purchase intention are mediated by youth's perceived usefulness of AI in the context of AI-powered online junk food purchase.

H₁₀: The relationships between the [a] level of exposure or knowledge of AI and [b] the level of socialisation effect or food marketing of AI, and the purchase intention are mediated by youth's perceived ease-of-use of AI in the context of AI-powered online junk food purchase.

4. Research Methodology

4.1 Sampling and procedures.

The population of this study includes Youth consumers who has age between 16 to 27 and engage in online purchases. The sampling method adopted is convenience sampling. The sample size consists of 200 young people. The Google Form-based questionnaire was distributed to the respondents through email and WhatsApp. Table 4.1 shows the demographic profile of the respondents, with regard to gender- 200 respondents were constituted, of which 103 (51.5%) were male and 97 (48.5%) female. With respect to the level of education, most of the respondents belong to the lower and mid-level educational levels. Precisely, 84 respondents (42.05%) had completed higher secondary education (12th class), and 66 respondents (33.05%) had completed their graduation. Also, a total of 49 respondents (24.5%) had postgraduate qualifications and only 1 respondent (0.5%) had a PhD or above qualification. This population breakdown is especially applicable in investigating how digital platforms using artificial intelligence affect the behaviour of consuming junk food, since younger and more moderately educated people are more prone to be involved with the online platforms that are AI-driven.

Table 4.1: Demographic profile of the respondents

Variable	Category	No.	%	Cumulative %
Gender	Male	103.00	51.50	51.50
	Female	97.00	48.50	100.00
	Total	200.00	100.00	—
Education	PhD or Higher	1.00	0.50	0.50
	Post Graduate	49.00	24.50	25.00
	Graduate	66.00	33.00	58.00
	Plus Two	84.00	42.00	100.00
	Total	200.00	100.00	—

Source: The authors' calculation based on primary data

4.2 Constructs, Variables and measurement

The present study examines the influence of AI on consumer behavior in online food purchasing by analyzing five major constructs: Level of Exposure/Knowledge to AI (LEORK), Socialization Effect/Food

Marketing (SEFM), Perceived Ease of Use of AI (PEU), Perceived Usefulness of AI (PU), and Purchase Intention (PI). The constructs, questions under each construct are explained in appendix 1. The questionnaire consists of 48 questions to measure the items in a five point Likert Scale.

4.3 Reliability, Convergent Validity and Discriminant validity.

It is essential to ensure the reliability, convergent and discriminant validity of data to apply SEM and smart PLS tools to test hypothesis. These concepts form the foundation of a strong measurement model. Reliability refers to consistency and stability of measurement. If a construct is reliable, there should be internal consistency. In this study we used Cronbach's Alpha (α), Composite Reliability (ρ_c) and Composite Reliability (ρ_a) to measure the consistency of constructs. A value of more than 0.70 in these three tests is considered as acceptable and data is consistent. Convergent validity refers to the degree to which multiple indicators of a construct agree or converge. It measured using factor loading and Average Variance Extracted (AVE). the factor loading value above 0.5 is acceptable level of relationship of items with constructs. Higher the loading, stronger the relationship. Discriminant validity examines and ensure that each construct is different from other constructs and each construct capture a unique concept. This study used Fornell-Larcker static to examine the discriminant validity.

4.4 Structural Equation Modelling (SEM)

SEM is an advanced statistical technique used to analyze relationships between variables, especially when those variables are latent. SEM combines Factor Analysis to measure latent variables and Regression/Path Analysis to test relationships. Basic Components of SEM are Latent Variables (Constructs), which are not directly observed. In our study, Level of Exposure/Knowledge to AI (LEORK), Socialization Effect/Food Marketing (SEFM), Perceived Ease of Use of AI (PEU), Perceived Usefulness of AI (PU), and Purchase Intention (PI) are the constructs. The study measured these constructs through 5-point Likert-scale questions.

The structural model shows relationships between constructs by using Path coefficients (β), R-squared, and Significance (p-values). This study applies Partial Least Squares SEM (PLS-SEM) available in SmartPLS to study the relationship between the variables as shown in Figure 3.1 (Conceptual framework). This model extends the Technology Acceptance Model (TAM) by adding LEORK (knowledge dimension) and SEFM (social & marketing influence). Hence, the flow becomes External Factors (LEORK, SEFM) to Psychological Perceptions (PEU, PU) and Behaviour (PI). The model proposes that Learning/Knowledge and Social/Family factors influence Purchase Intention both directly and indirectly through Perceived Ease of Use and Perceived Usefulness. Perceived Ease of Use also affects Perceived Usefulness, which further drives Purchase Intention.

5. Analysis and Results

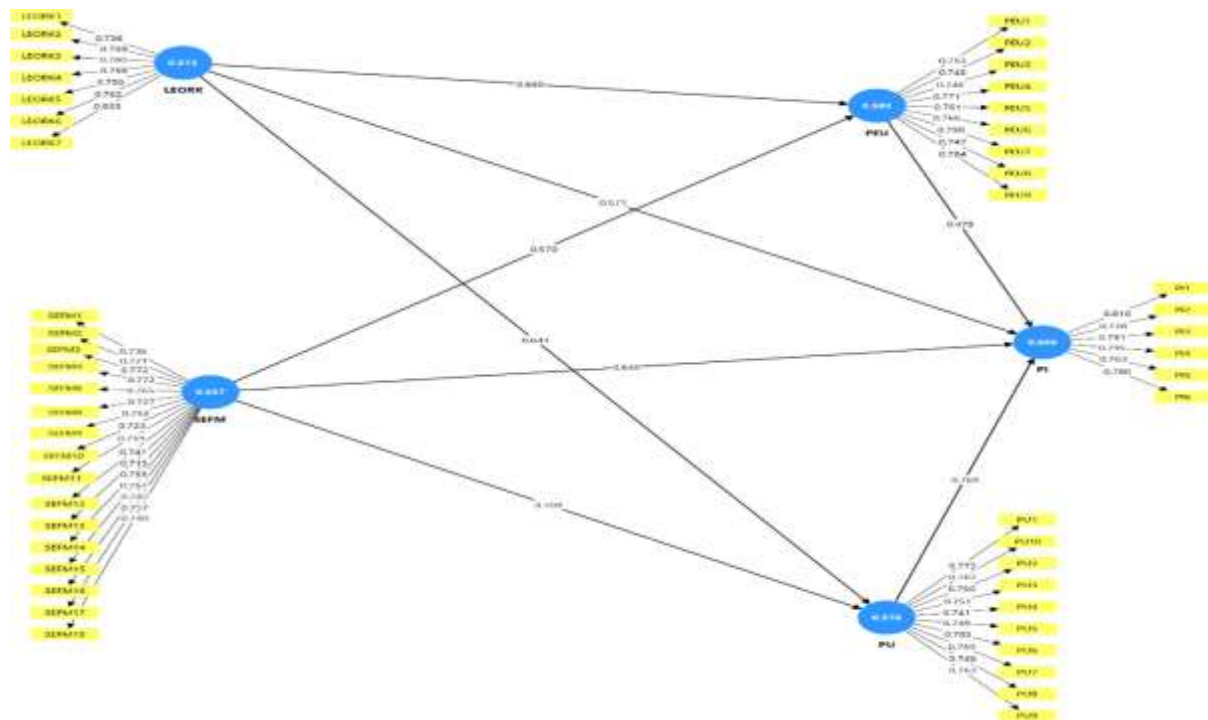
Table 5.1: Descriptive Statistics for Age (N = 200)

Variable	M	SD	Skewness	Kurtosis
Age	19.62	2.80	1.33	3.56

Source: The authors' calculation based on primary data

Table 2 provides the descriptive statistics of age. As shown in the results, the average age of the respondents is 19.62 years with a standard deviation of 2.80, which indicates that the sample is mainly composed of late adolescents and young adults. It is in line with the subject matter of the research on youth within the framework of artificial intelligence-based digital spaces.

Figure 1: Structural Model Linking AI-Based Digital Influence Constructs (LEORK, SEFM) with Perceived Ease of Use, Usefulness, and Purchase Intention



Source: Author's compilation based on existing literature.

Table 5.2: Reliability and Convergent Validity of Constructs

	Cronbach's alpha	Composite reliability(rhoa)	Composite reliability (rhoc)	Average variance (AVE)
LEORK	0.894	0.896	0.917	0.613
PEU	0.911	0.911	0.926	0.583
PI	0.871	0.873	0.903	0.608
PU	0.919	0.919	0.932	0.578
SEFM	0.947	0.947	0.948	0.557

Source: The authors' calculation based on primary data

Table 5.2 shows the reliability and convergent validity of the constructs. Most of the values are consistent with the rule of thumb as suggested by Hair et al. (2006). Cronbach alpha and composite reliability (ρ_a and ρ_c) were used to evaluate internal consistency reliability. The constructs were all found to be very reliable, with Cronbach's alpha values of 0.871 to 0.947 being above the suggested value of 0.70. On the same note, composite reliability values (0.903-0.948) were high and therefore, there was high internal consistency in all constructs. The average variance extracted (AVE) assessed convergent validity. The values of the AVE were between 0.557 and 0.613 which is more than the minimum acceptable value of 0.50 and as such sufficient convergent validity is confirmed. The findings suggest that the constructs of LEORK, PEU, PI, PU, and SEFM have high reliability and acceptable convergent validity, which proves the relevance of the measurement model.

Table 5.3: Discriminant validity using Fornell and Lacker criterion

	LEORK	PEU	PI	PU	SEFM
LEORK	0.783				
PEU	0.660	0.764			
PI	0.571	0.478	0.78		
PU	0.643	0.589	0.769	0.76	
SEFM	0.724	0.57	0.649	0.709	0.746

Source: The authors' calculation based on primary data

Table 5.3 shows the evaluation of the discriminant validity based on the Fornell-Larcker criterion. By this standard, the square root of the average variance extracted (AVE) of any particular construct must be larger than its correlations with other constructs. The diagonal lines in the table show the square root of the AVE of each construct. As seen, all constructs (LEORK 0.783), PEU (0.764), PI (0.780), PU (0.760), SEFM (0.746)) have higher values of the diagonal than their corresponding inter-constructs. The findings affirm that the constructs are all empirically different, which means that the discriminant validity has been satisfactorily met by the measurement model.

Table 5.4: Result of the Heterotrait–Monotrait (HTMT) test

	LEORK	PEU	PI	PU
PEU	0.730			
PI	0.645	0.535		
PU	0.708	0.643	0.858	
SEFM	0.785	0.612	0.713	0.759

Source: The authors' calculation based on primary data

Table 5.4 shows the evaluation of the discriminant validity in terms of the Heterotrait-Monotrait ratio (HTMT). The rule of thumb for this test is based on Kline (2012). The values of the HTMT should meet the criteria, according to which the values should not exceed the conservative threshold of 0.85 (or 0.90 in more generous instances) to ensure discriminant validity. The table indicates that the range of values of the constructs in terms of HTMT is 0.535 to 0.858. The majority of the values are less than the suggested value of 0.85, which implies good discriminant validity. Even though the HTMT between PU and PI (0.858) is slightly higher than the conservative value of 0.85, it is still acceptable. The findings reveal that the constructs exhibit reasonable levels of discriminant validity, and the measurement model satisfies the HTMT test.

Table 5.5: Outer loadings

	LEORK	PEU	PI	PU	SEFM
LEORK1	0.736				
LEORK2	0.789				
LEORK3	0.780				
LEORK4	0.788				
LEORK5	0.786				
LEORK6	0.762				
LEORK7	0.835				
PEU1		0.753			
PEU2		0.745			
PEU3		0.748			
PEU4		0.771			
PEU5		0.761			
PEU6		0.766			
PEU7		0.798			
PEU8		0.747			
PEU9		0.784			
PI1			0.810		
PI2			0.738		
PI3			0.791		
PI4			0.795		
PI5			0.763		
PI6			0.780		
PU1				0.773	
PU10				0.787	

PU2	0.750
PU3	0.751
PU4	0.741
PU5	0.749
PU6	0.785
PU7	0.759
PU8	0.746
PU9	0.763
SEFM1	0.736
SEFM10	0.723
SEFM11	0.759
SEFM12	0.741
SEFM13	0.715
SEFM14	0.755
SEFM15	0.757
SEFM16	0.742
SEFM17	0.757
SEFM18	0.740
SEFM2	0.721
SEFM3	0.772
SEFM4	0.772
SEFM6	0.765
SEFM8	0.727
SEFM9	0.753

Source: The authors' calculation based on primary data

The table 5.5 shows the outer loading of all measurement items on their constructs. When the factor loadings are greater than the suggested factor loading of 0.70, then the indicator reliability is deemed to be satisfactory. The findings show that every item has a high loading to its constructs with a range of scores of between 0.715 and 0.835. In particular, the loadings of the items that measure LEORK are between 0.736 and 0.835, which indicates high reliability of the indicators. On the same note, PEU and PI have a range of 0.745 to 0.798, and 0.738 to 0.810 respectively, which results in consistent and reliable measurement. The loadings of the construct PU are within the range of 0.741 to 0.787, and they are all above the acceptable level. The SEFM construct also shows acceptable loadings, with the lower extremes of 0.715-0.772, although its indicators were relatively many. Notably, all the items have a score that is not less than the critical cutoff of 0.70 and thus, none of the items are to be dropped. The results indicate that all indicators have sufficient indicator reliability, which confirms the strength of the measurement model.

Table 5.6: R²

	R-square	R-square adjusted
PEU	0.453	0.450
PI	0.615	0.611
PU	0.539	0.536

Source: The authors' calculation based on primary data

Table 5.6 shows the coefficient of determination (R²) and adjusted R² of the endogenous constructs. The value of R² is used to show the percentage of variance in the dependent construct that the predictor variables explain. The findings indicate that the R² value of the perceived ease of use (PEU) is 0.453 (adjusted R² = 0.450), which means that the antecedents of PEU explain an approximation of 45.3 percent of its variance. This is an average degree of explanatory power. Regarding the perceived usefulness (PU), we find the value of R² = 0.539 (adjusted R² = 0.536) which indicates that 53.9 percent variance in PU can be explained by the model. This is an indication of a moderate to a high degree of explanation. Construct

purchase intention (PI) has a value of $R^2 = 0.615$ (adjusted $R^2 = 0.611$), which shows that 61.5 percent of PI variance is attributed to predictors. This is evidence of a high degree of explanatory power. The model depicts moderate to strong predictive power where purchase intention is the most powerful followed by perceived usefulness and perceived ease of use.

Table 5.7: F^2

	PEU	PI	PU
LEORK	0.234	0.004	0.076
PEU		0.001	
PU		0.433	
SEFM	0.033	0.033	0.271

Source: The authors' calculation based on primary data

Table 5.7 shows the values of effect size (f^2), which determines the contribution made by each exogenous construct to the R^2 value of the endogenous constructs. By the accepted rules, the f^2 of 0.02, 0.15, and 0.35 are a small, medium, and large effect respectively. The findings suggest that LEORK moderately influences PEU ($f^2 = 0.234$) and has a small influence on PU ($f^2 = 0.076$) though its impact on PI is insignificant ($f^2 = 0.004$). PEU has a small impact on PI ($f^2 = 0.001$), meaning that it does not significantly help explain purchase intention. PU, on the contrary, has a significant impact on PI ($f^2 = 0.433$), which indicates that the perceived usefulness is the most important predictor of purchase intention in the model. Regarding SEFM, it has small effects on PEU ($f^2 = 0.033$) and PI ($f^2 = 0.033$), and a medium effect on PU ($f^2 = 0.271$). The results indicate that PU is the most powerful predictor of PI, and LEORK and SEFM have moderate effects on PU and PEU, and PEU does not have a significant effect on PI.

Table 5.7: Results of SEM (Hypotheses testing)

Hypothesis	Path	β (Direct)	β (Indirect)	β (Total)	t-value	p-value	Mediation Type	Decision
H1	LEORK → PU	0.272***	—	0.272**	5.094	<.001	—	Accepted
H2	LEORK → PEU	0.518***	—	0.518**	10.449	<.001	—	Accepted
H3	LEORK → PI	0.060	0.153***	0.213**	1.168 (direct)	0.243	Full Mediation (via PU)	Not Accepted (Direct), Accepted (Indirectly)
H4	SEFM → PI	0.184***	0.311***	0.495**	3.779	<.001	Partial Mediation (via PU)	Accepted
H5	SEFM → PU	0.512***	—	0.512**	9.871	<.001	—	Accepted
H6	SEFM → PEU	0.195***	—	0.195**	3.557	<.001	—	Accepted
H7	PU → PI	0.618***	—	0.618**	14.02	<.001	—	Accepted
H8	PEU → PI	-0.030	—	-0.030	0.661	0.509	—	Not Accepted
H9a	LEORK → PU → PI	—	0.168***	—	4.708	<.001	Full Mediation	Accepted
H9b	SEFM → PU → PI	—	0.317***	—	8.025	<.001	Partial Mediation	Accepted
H10a	LEORK → PEU → PI	—	-0.016	—	0.658	0.511	No Mediation	Not Accepted
H10b	SEFM → PEU → PI	—	-0.006	—	0.623	0.533	No Mediation	Not Accepted

Notes: The table below demonstrates the findings of the structural model with Partial Least Square (PLS) version 4. the sample size is 200. The symbols *, **, and *** are indications of significance at 10, 5 and 1 percent respectively.

Source: The authors' calculation based on primary data

6. Discussions of findings

These findings suggest that level of exposure and knowledge of AI (LEORK) positively affects perceived usefulness (PU) significantly, $\beta = 0.272$, $t = 5.094$, $p < .001$. Therefore, the hypothesis H1 is confirmed, and it is presumed that the younger people are exposed to AI, the more they perceive it as useful in the context of making online purchases of junk food using AI. LEORK shows a significant positive effect on perceived ease of use (PEU), $\beta = 0.518$, $t = 10.449$, $p < .001$. Hence, the H2 is accepted, which shows that the higher the exposure to AI, the better perceived ease of use in young people. The direct effect of LEORK on purchase intention (PI) is not significant, $\beta = 0.060$, $t = 1.168$, $p = .243$. Therefore, the H3 is not accepted in the direct relationship. The overall impact ($\beta = 0.213$) is however an indication of indirect impact, which implies mediation effects.

The purchase intention is strongly positively affected by socialisation effect and food marketing (SEFM) $\beta = 0.184$, $t = 3.779$, $p < .001$. H4 is therefore supported which means that AI-based socialisation and marketing play a critical role in determining the purchase intentions of the youth. SEFM has a large and positive impact on perceived usefulness, $\beta = 0.512$, $t = 9.871$, $p < .001$. Thus, the H5 hypothesis is approved, and it can be concluded that AI-based marketing and socialisation increase the perceived usefulness. The positive influence of SEFM on perceived ease of use is also significant, $\beta = 0.195$, $t = 3.557$, $p < .001$. Hence, H6 is supported.

The perceived usefulness significantly influences purchase intention, with a positive value, $\beta = 0.618$, $t = 14.020$, $p < .001$. Accordingly, H7 is accepted, which means that PU is a significant predictor of purchase intention. The easiness of use is not a significant factor in purchase intention, $\beta = -0.030$, $t = 0.661$, $p = .509$. As such, H8 is not supported.

6.1 Mediation Effects (H9-H10)

The indirect effect of LEORK on PI via PU is significant, $\beta = 0.168$, $t = 4.708$, $p < .001$. The fact that the direct effect is not significant and the indirect effect is significant means full mediation. Thus, the hypothesis H9a is confirmed, which indicates that PU is a complete mediator of the relationship between LEORK and PI. The indirect effect of SEFM on PI through PU is significant, $\beta = 0.317$, $t = 8.025$, $p < .001$. Since both of the direct and indirect effects are strong, this implies partial mediation. Thereby, H9b is justified.

The indirect effect of LEORK on PI via PEU is not significant $\beta = -0.016$, $t = 0.658$, $p = .511$. Thus, H10a is not accepted, meaning that there is no mediation. Similarly, the indirect effect of SEFM on PI through PEU is not significant, $\beta = -0.006$, $t = 0.623$, $p = .533$. Therefore, the H10b is not upheld, which proves the absence of mediation.

The results reveal that perceived usefulness (PU) has a significant mediating role, but perceived ease of use (PEU) has no significant influence on purchase intention and it does not mediate relationships. The impact of AI and marketing effects on purchase intention is mainly based on usefulness and not ease of use.

7. Conclusion and policy implications

The present research gives empirical support to the mechanism by which Artificial Intelligence (AI) influences the intentions to consume junk foods among young people. Combining AI-specific variables with the TAM theory, this study finds that digital influence could not be simply a question of technological exposure, but a complex psychological process that is guided by Perceived Usefulness (PU). The results show that, although the youth are extremely exposed to marketing based on AI, the exposure does not directly translate into purchase intentions. Instead, it has to be filtered on a perception of utility first. More importantly, the research is still finding a generational change in technology acceptance: Perceived Ease of Use (PEU) which has long been a staple of technology adoption is not a consideration among young people who are digital natives. The ease of use of AI interfaces is not a behavioral incentive but more a natural expectation of this demographic. Thus, the model of social influence enhanced with the help of AI algorithms (SEFM) becomes a powerful tool, which forms virtual spaces where the consumption of junk food is seen as normal and healthy.

Theoretically, the study advances the development of TAM in the era of AI, where researchers should focus more on the variables based on utility, rather than on the variables based on usability, in the research of digital natives. In essence, the findings can be translated into a call to action among the policymakers of public health. Old-fashioned digital literacy trainings, which are based on how to use the internet safely, are not enough. The change in interventions should be shifted to algorithmic literacy, where young people

are taught how to critically assess any attempt to personalize usefulness by AI to influence them to adopt unhealthy eating habits.

8. Limitations and scope for further research

Despite, the measurement model is highly reliable and valid, the study has weaknesses in that it is a cross-sectional study and that the data collected is self-reported, and it is therefore prone to social desirability bias. The future studies are to use longitudinal designs in order to monitor the long-term effect of AI influence on real BMI and metabolic health. Moreover, one could conduct experimental research to determine whether the use of so-called Healthy AI Nudges, i.e., the reuse of the same utility-driven algorithms applied to nutritious foods, can help reverse the trend of promoting digital junk food at present.

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Appendix

Research Instrument and Construct Operationalization

All items were measured on a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Table I: Constructs, Measurement Items, and Sources

Construct	Item Code	Measurement Item	Source(s)
Level of Exposure/ Knowledge to AI (LEORK)	LEORK1	I consider myself very uninformed about what artificial intelligence means.	[12, 15,7,6,3]
	LEORK2	I know some basics about AI, but I have a lot to learn.	
	LEORK3	I have an average knowledge of AI and can explain basic concepts.	
	LEORK4	I have advanced knowledge of AI and a thorough understanding of how it works.	
	LEORK5	I consider myself an expert in AI and can discuss advanced applications.	
	LEORK6	I follow various AI applications to purchase food items.	
	LEORK7	I believe AI can bring significant improvements to online shopping.	
Socialization Effect/ Food Marketing (SEFM)	SEFM1	I use AI-assisted apps and advertisements (deals, coupons) for food.	[15,8, 9,16,13,11]
	SEFM2	I like to follow influencers' choices of food products.	
	SEFM3	[Platform Preference]: In which online platform do you find junk food influencers mostly?	
	SEFM4	[Platform Preference]: In which online platform do you find more junk food products or brands?	
	SEFM6	Marketing Techniques for junk foods in different online platforms [Use of influencers]	
	SEFM8	Marketing Techniques for junk foods in different online platforms [Teen themes]	

	SEFM9	Marketing Techniques for junk foods in different online platforms [Price promotions]	
	SEFM10	Marketing Techniques for junk foods in different online platforms [Games or activities]	
	SEFM11	Marketing Techniques for junk foods in different online platforms [Music or graphics]	
	SEFM12	Marketing Techniques for junk foods in different online platforms [Appeals to healthfulness]	
	SEFM13	Marketing Techniques for junk foods in different online platforms [Appeals to social enhancements]	
	SEFM14	Marketing Techniques for junk foods in different online platforms [Appeals to social enhancements]	
	SEFM15	Junk food categories mostly seen in different online platforms [Fast food items]	
	SEFM16	Junk food categories mostly seen in different online platforms [Soft drinks]	
	SEFM17	Junk food categories mostly seen in different online platforms [Snacks]	
	SEFM18	Junk food categories mostly seen in different online platforms [Candy]	
Perceived Ease of Use (PEU)	PEU1	AI marketing technology helps me accurately retrieve items via words/voice.	[5,12,15,19,17]
	PEU2	The platform recommends food brands I may buy (e.g., “guess what you like”).	
	PEU3	I follow chatbot suggestions like “Would you like to try our new spicy fries?”	
	PEU4	I like comforting food ads like pizza or chocolate when I’m stressed.	
	PEU5	I have used voice assistants (e.g., Siri, Google Assistant) for food purchases.	
	PEU6	When AI provides alternatives, shopping doesn’t require significant mental effort.	
	PEU7	AI simplifies shopping by suggesting products to me.	
	PEU8	It’s simple to understand how to use AI-optimized shopping apps.	
	PEU9	AI-powered apps and stores are easy to use.	
Perceived Usefulness (PU)	PU1	AI is an effective tool for personalizing offers and customer experiences.	[5,12,15,21,20]
	PU2	AI provides a personalized shopping interface based on my preferences.	
	PU3	I follow AI applications like voice recognition for food purchases.	
	PU4	AI helps me find practical food choices.	
	PU5	AI-supported online shopping makes me feel happy.	
	PU6	AI gives me more food choices I wish to taste.	
	PU7	I enjoy AI-created TikTok videos showing fast food in fun ways.	
	PU8	I see AI in marketing as innovative and beneficial.	
	PU9	AI can significantly improve junk food shopping strategies.	

	PU10	I have a positive perception of AI in online shopping.	
Purchase Intention (PI)	PI1	I am willing to buy products that use AI in sales in the near future.	[12,15,23,22,2]
	PI2	I consider recommending others to buy products that use AI in sales.	
	PI3	I would consider buying a product that benefits from AI technologies.	
	PI4	I tend to visit online shopping sites that use AI in sales.	
	PI5	I end up buying products from online stores that have AI-based technology.	
	PI6	I am willing to spend more on purchases through AI-powered stores.	