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AI-Driven Personalisation

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AI-Driven Hyper-Personalisation and Consumer Usage Behaviour in Food Delivery Applications

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This study explores the effect of AI-driven hyper-personalisation on the behaviour of food delivery app users. Personalisation is a crucial element of customer experience that shapes user interactions and perceptions of service value. AI-driven hyper-personalisation uses user data and behaviour patterns to provide tailored recommendations and offers, making decision-making easier. This approach aims to increase consumer engagement. The focus is on how this hyper-personalisation affects food delivery app usage, examining perceived relevance, trust in AI, ease of decision-making, and the role of cognitive load. A quantitative research approach was adopted. Data was collected from 200 active users of Swiggy and Zomato and analysed using descriptive analysis, reliability analysis, correlation, regression, and mediation analysis. Additionally, the study may have some sample selection bias because the respondents were only active users of Swiggy and Zomato, which may not represent all food delivery app users. Findings indicate that trust in AI recommendations and perceived ease of decision-making significantly enhance consumer usage behaviour, whereas perceived relevance alone does not significantly influence behavioural outcomes. Cognitive load plays a significant partial mediating role between trust, decision ease, and usage behaviour. The study also highlights the importance of developing AI systems that are easy to understand, simple to use, and capable of reducing users' mental effort while making decisions.

Keywords: ai-driven personalisation, hyper-personalisation, cognitive load, food delivery applications, consumer usage behaviour, trust in ai, perceived decision ease, perceived relevance

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1. Introduction

The rise of Artificial Intelligence (AI) has profoundly altered the dynamics of digital consumer interactions, especially within service-oriented industries like food delivery applications. As AI technology advances with machine learning, predictive analytics, and real-time data processing, digital platforms now offer highly sophisticated, AI-driven, hyper-personalised experiences that greatly enhance user satisfaction and engagement.

Hyper-personalisation represents a significant advancement in marketing strategies, moving away from traditional segmentation methods that group users based on broad demographic characteristics. Instead, it focuses on individual user experiences, employing real-time behavioural data and contextual information to create tailored experiences. Advanced algorithms process users' past interactions, preferences, and immediate context to provide recommendations that are not only timely but also highly relevant to their unique needs. In food delivery applications, AI systems analyse previous orders, preferred cuisines, browsing behaviours, ordering times, and geographic location to curate personalised menus and targeted offers.

While the advantages of AI-driven systems are evident, a growing concern is the complexity they introduce to consumer cognition and decision-making. When the volume of recommendations becomes excessive or poorly organised, it can lead to choice overload, increasing cognitive strain. Cognitive load, defined as the mental effort required to process information and make decisions, plays a significant role in users' interactions with digital platforms. AI-driven personalisation can both reduce cognitive load (by streamlining choices) and inadvertently increase it (by overwhelming users with information).

This study explores the impact of AI-driven hyper-personalisation on consumer behaviour in food delivery applications, emphasising three pivotal determinants: perceived relevance of personalised recommendations, trust in AI-generated suggestions, and perceived ease of decision-making. Cognitive load is conceptualised as a mediating variable that explains how these personalisation factors shape consumer usage behaviour.

1.1 Objectives of the Study

The primary objective is to examine the influence of AI-driven hyper-personalisation on consumer usage behaviour in food delivery applications by analysing how personalisation factors affect cognitive load and how cognitive load, in turn, influences behavioural engagement.

Secondary objectives include:

(1) To examine the effect of perceived relevance on cognitive load and consumer usage behaviour;
(2) To evaluate how trust in AI recommendations influences cognitive load and consumer usage behaviour;
(3) To assess the role of perceived decision ease in shaping cognitive load and consumer usage behaviour; and
(4) To examine the mediating role of cognitive load between personalisation factors and consumer usage behaviour.

2. Review of Literature

The rapid expansion of digital technologies has significantly transformed consumer behaviour in the online marketplace, particularly in the food delivery industry. Modern consumers increasingly depend on applications such as Zomato, Swiggy, and Uber Eats to discover restaurants, compare alternatives, receive recommendations, and complete purchases conveniently.

2.1 Hyper-Personalisation

Hyper-personalisation refers to the use of AI-driven systems that analyse consumer data such as browsing history, previous orders, cuisine preferences, location, and spending patterns to deliver highly tailored recommendations and offers (Adomavicius & Tuzhilin, 2005). Personalised recommendations improve consumer decision-making by increasing relevance and efficiency in online platforms (Tam & Ho, 2006). Highly relevant personalised content enhances user engagement (Bleier & Eisenbeiss, 2015). AI-driven personalisation also improves customer satisfaction and service efficiency (Huang & Rust, 2021). Recent studies found that AI-powered personalised recommendations significantly improve customer experience and engagement in food delivery platforms (Wang et al., 2025).

2.2 Perceived Relevance

Perceived relevance refers to the extent to which consumers believe that recommendations match their personal needs and preferences (Xu et al., 2014). Relevant recommendations improve perceived usefulness and reliance on recommendation systems (Xu et al., 2014). They also reduce search effort, increase satisfaction, and improve decision confidence (Jannach & Adomavicius, 2016). Li et al. (2021) found that perceived relevance significantly influences user acceptance of AI-driven recommendations. Recent research indicates that AI-based personalised recommendations improve relevance perception and increase user engagement in online food-ordering platforms (Khan, 2025).

2.3 Trust in AI Recommendations

Trust in AI recommendations refers to the degree to which users believe AI-generated suggestions are reliable and beneficial for decision-making (Gefen et al., 2003; Shin, 2021). Trust significantly influences adoption and continued usage behaviour in online systems (Gefen et al., 2003). Recommendation transparency and explanations improve trust and usage intention (Zhang & Benbasat, 2004). Dietvorst et al. (2015) identified algorithm aversion when users lose trust after visible algorithmic errors. Recent studies show that trust in AI systems significantly affects consumer acceptance and loyalty in AI-enabled digital environments (Hassan et al., 2025).

2.4 Perceived Decision Ease

Perceived decision ease refers to the extent to which users feel that a platform simplifies purchasing decisions and reduces complexity (Häubl & Trifts, 2000). Recommendation systems reduce consumer effort and improve decision quality (Häubl & Trifts, 2000). Xiao and Benbasat (2007) reported that recommendation systems lower cognitive effort and improve convenience in online decision-making. Gao et al. (2021) further found that perceived decision ease significantly influences the adoption of AI-based services. Recent studies indicate that AI-enabled recommendation systems simplify food-ordering decisions and improve user convenience through intelligent recommendations and predictive ordering features (Patel et al., 2025).

2.5 Cognitive Load

Cognitive load refers to the mental effort required to process information and make decisions (Sweller, 1988). In food delivery applications, users are exposed to multiple restaurants, cuisines, reviews, ratings, and offers, which may create confusion and decision fatigue. Wang et al. (2021) found that higher cognitive load negatively affects user acceptance of AI systems, while Dabholkar and Sheng (2012) observed that cognitive load influences reliance on recommendation systems. Recent studies suggest that well-designed AI recommendation systems help reduce cognitive burden and improve user experience during online decision-making (Shamszare & Choudhury, 2023).

2.6 Consumer Usage Behaviour

Consumer usage behaviour refers to the frequency and extent of users' interaction with a digital platform, including repeat usage, responsiveness to recommendations, and customer loyalty (Venkatesh et al., 2003). Positive perceptions regarding usefulness and ease of use significantly influence actual usage behaviour (Venkatesh et al., 2003). AI-enabled recommendation systems also positively influence consumer engagement and platform usage (Alalwan et al., 2021). Pizzi et al. (2021) found that AI personalisation strengthens customer relationships and engagement. Recent studies further show that AI-powered features such as personalised recommendations and chatbot interactions positively influence repeat usage and customer engagement in food delivery applications (Al Maalouf et al., 2025).

2.7 Conceptual Framework and Hypotheses

The conceptual framework proposes that hyper-personalisation in food delivery applications influences consumer usage behaviour through three behavioural dimensions: perceived relevance (PR), trust in AI recommendations (TR), and perceived decision ease (DSE), mediated by cognitive load (CL). The following hypotheses were developed:

H1: Perceived relevance has a significant positive effect on consumer usage behaviour.
H2: Trust in AI recommendations has a significant positive effect on consumer usage behaviour.
H3: Perceived decision ease has a significant positive effect on consumer usage behaviour.
H4: Perceived relevance significantly affects cognitive load.
H5: Trust in AI recommendations significantly affects cognitive load.

H6: Perceived decision ease significantly affects cognitive load.
H7: Cognitive load significantly affects consumer usage behaviour.
H8: Cognitive load mediates the relationship between perceived relevance and consumer usage behaviour.
H9: Cognitive load mediates the relationship between trust in AI recommendations and consumer usage behaviour.
H10: Cognitive load mediates the relationship between perceived decision ease and consumer usage behaviour.

3. Research Methodology

The study adopts a quantitative, cross-sectional research design using both descriptive and explanatory approaches. Hypotheses were developed based on the Technology Acceptance Model (TAM) and Cognitive Load Theory. Primary data were collected via a structured questionnaire administered through Google Forms to 200 active users of food delivery applications (Swiggy and Zomato), using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). A non-probability convenience sampling technique was employed.

The questionnaire adapted validated scales from prior literature: perceived relevance from (Tam and Ho 2006) and (Xu et al. 2011); trust in AI recommendations from (Gefen et al. 2003) and (McKnight et al. 2002); perceived decision ease from Davis (1989); cognitive load from (Sweller 1988) and (Paas and Van Merriënboer 1994); and consumer usage behaviour from (Venkatesh et al. 2003) and (Bhattacherjee 2001).

Data were analysed using Jamovi and Microsoft Excel. Statistical tools applied included descriptive statistics, Cronbach's alpha reliability analysis, independent samples t-test, one-way ANOVA (Welch's), multiple linear regression, and mediation analysis with bootstrapping to test indirect effects.

4. Data Analysis and Results

4.1 Demographic Profile of Respondents

The sample of 200 respondents was predominantly young, with 74.5% belonging to the 21–25 years age group, followed by 13.5% in the 26–30 years category, while only a small percentage belonged to other age groups. Male respondents constituted 59.5% of the sample, whereas females accounted for 40.5%. In terms of occupation, the majority of respondents were students (79.5%), followed by working professionals (19.5%) and self-employed individuals (1.0%). Regarding educational qualification, 57.5% of the respondents were postgraduates and 42.5% were undergraduates. Concerning app usage frequency, 36.0% of respondents used food delivery applications occasionally, 35.5% used them 2–3 times a week, 21.5% used them once a week, and 7.0% used them daily. Among the food delivery platforms, Swiggy emerged as the most frequently used application (61.0%), followed by Zomato (34.5%), Uber Eats (3.5%), and Eat Sure (1.0%).

Demographic Variable	Category	Count	% of Total
Age Group	Below 20 years	19	9.5%
	21–25 years	149	74.5%
	26–30 years	27	13.5%
	31–35 years	2	1.0%
	Above 35 years	3	1.5%
Gender	Male	119	59.5%
	Female	81	40.5%
Occupation	Student	159	79.5%
	Working Professional	39	19.5%
	Self-Employed	2	1.0%
Education	Postgraduate	115	57.5%
	Undergraduate	85	42.5%
Frequency of Using Food Delivery Apps	Daily	14	7.0%
	2–3 times a week	71	35.5%
	Once a week	43	21.5%
	Occasionally	72	36.0%
Most Frequently Used Food Delivery App	Swiggy	122	61.0%
	Zomato	69	34.5%
	Eat Sure	2	1.0%
	Uber Eats	7	3.5%

Table 1: Demographic Profile of Respondents

4.2 Reliability Analysis

Cronbach's alpha was computed for all constructs. All values exceeded the recommended threshold of 0.70, confirming acceptable to high internal consistency and suitability for further analysis.

Construct	Cronbach's α
Perceived Relevance	0.849
Trust in AI Recommendations	0.857
Perceived Decision Ease	0.822
Cognitive Load	0.783
Consumer Usage Behaviour	0.797

Table 2: Reliability Analysis (Cronbach's Alpha)

4.3 Inferential Analysis: T-Test and ANOVA

An independent samples t-test was conducted to examine gender-based differences. All p-values across the five constructs exceeded 0.05 (Perceived Relevance: $p = 0.149$; Trust in AI: $p = 0.889$; Perceived Decision Ease: $p = 0.736$; Cognitive Load: $p = 0.331$; Consumer Usage Behaviour: $p = 0.864$), indicating no statistically significant differences between male and female respondents. Similarly, Welch's one-way ANOVA revealed no significant differences across age groups (all $p > 0.05$). These findings suggest that demographic characteristics do not significantly shape user perceptions or behaviour, implying a level of universality in how users interact with AI-driven personalisation features.

4.4 Multiple Linear Regression Analysis

Multiple linear regression was conducted with Consumer Usage Behaviour (USB) as the dependent variable and Perceived Relevance (PR), Trust in AI Recommendations (TR), and Perceived Decision Ease (DSE) as independent variables. The model demonstrated strong explanatory power ($R = 0.811$, $R^2 = 0.658$), indicating that approximately65.8% of the variance in consumer usage behaviour is explained by the model.

Predictor	β	SE	t	p-value	Decision
Intercept	0.652	0.192	3.401	< .001	—
Perceived Relevance (PR)	-0.008	0.048	-0.159	0.874	Not Significant
Trust in AI (TR)	0.422	0.064	6.613	< .001	Significant
Perceived Decision Ease (DSE)	0.411	0.070	5.862	< .001	Significant

Table 3: Multiple Regression Coefficients (Dependent Variable: Consumer Usage Behaviour)

Trust in AI Recommendations ($\beta = 0.422$, $p < 0.001$) and Perceived Decision Ease ($\beta = 0.411$, $p < 0.001$) emerged as highly significant positive predictors of consumer usage behaviour. In contrast, Perceived Relevance ($\beta = -0.008$, $p = 0.874$) did not show a statistically significant effect. Accordingly, H2 and H3 are accepted, while H1 is rejected.

4.5 Mediation Analysis

Mediation analysis was conducted to examine whether Cognitive Load (CL) mediates the relationships between the independent variables and Consumer Usage Behaviour. Both direct and indirect effects were analysed, with bootstrapping used to assess the significance of indirect effects.

Path	Type	Estimate	β	p-value
PR ⇒ CL ⇒ USB	Indirect	0.014	0.015	0.359
TR ⇒ CL ⇒ USB	Indirect	0.112	0.124	< .001
DSE ⇒ CL ⇒ USB	Indirect	0.147	0.142	< .001
PR ⇒ CL	Component	0.042	0.046	0.349
TR ⇒ CL	Component	0.345	0.393	< .001
DSE ⇒ CL	Component	0.452	0.451	< .001
CL ⇒ USB	Component	0.325	0.315	< .001
PR ⇒ USB	Direct	-0.021	-0.023	0.640
TR ⇒ USB	Direct	0.310	0.343	< .001
DSE ⇒ USB	Direct	0.264	0.255	< .001

Table 4: Mediation Analysis Results (Mediator: Cognitive Load)

The indirect effects of TR ($\beta = 0.124$, $p < 0.001$) and DSE ($\beta = 0.142$, $p < 0.001$) on USB through CL are statistically significant, indicating that cognitive load significantly mediates these relationships (partial mediation). The indirect effect of PR ($\beta = 0.015$, $p = 0.359$) is not significant, indicating no mediation. The direct paths TR → CL and DSE → CL are both significant, and CL → USB is also significant, further supporting the partial mediation for trust and decision ease.

4.6 Hypothesis Testing Summary

Hypothesis	Statement	p-value	Decision
H1	PR → USB (positive effect)	0.874	Rejected
H2	TR → USB (positive effect)	< .001	Accepted
H3	DSE → USB (positive effect)	< .001	Accepted
H4	PR → CL	0.349	Rejected
H5	TR → CL	< .001	Accepted
H6	DSE → CL	< .001	Accepted
H7	CL → USB	< .001	Accepted
H8	CL mediates PR → USB	0.359	Rejected
H9	CL mediates TR → USB	< .001	Accepted (Partial)
H10	CL mediates DSE → USB	< .001	Accepted (Partial)

Table 5: Hypothesis Testing Summary

5. Findings and Discussion

The results of this study provide important insights into the determinants of consumer usage behaviour in AI-driven food delivery applications.

Trust in AI recommendations and perceived decision ease emerged as the most significant predictors of usage behaviour, while perceived relevance did not have a statistically significant effect. These findings challenge traditional assumptions in personalisation literature that often position relevance as the primary driver of engagement (Tam & Ho, 2006; Bleier & Eisenbeiss, 2015). Instead, the results suggest that relevance may function as a hygiene factor, a basic expectation rather than a differentiating motivator.

The significant positive effect of trust aligns with prior research by (Gefen et al. 2003), (Shin 2021), and Jiang et al. (2021), reinforcing that users must perceive AI systems as reliable and accurate before engaging with them. The significant role of perceived decision ease supports the Technology Acceptance Model (Venkatesh et al., 2003) and prior findings by (Häubl and Trifts 2000) and (Gao et al. 2021), underscoring that ease of use is a crucial determinant of technology adoption.

The mediation analysis confirms that cognitive load partially mediates the relationships between trust, perceived decision ease, and consumer usage behaviour. These findings align with Cognitive Load Theory (Sweller, 1988) and the work of (Dabholkar and Sheng 2012) and (Wang et al. 2021), demonstrating that AI systems that reduce mental effort and streamline decision-making are more effective in encouraging sustained usage. No mediation effect was observed for perceived relevance, further reinforcing its limited role in this context. The absence of significant demographic effects suggests that behavioural responses are more strongly influenced by psychological and usability factors than by user characteristics such as age or gender.

6. Conclusion

This study concludes that consumer behaviour in AI-driven food delivery applications is primarily shaped by trust in AI recommendations and perceived decision ease, rather than by perceived relevance. Cognitive load serves as a significant partial mediating mechanism through which trust and decision ease influence behavioural outcomes. The regression model explains approximately 65.8% of the variance in consumer usage behaviour, confirming the strong explanatory power of the selected variables.

The findings carry important theoretical and managerial implications. Theoretically, the study extends existing frameworks by introducing cognitive load as a mediating mechanism and challenges the primacy of relevance in personalisation models. Managerially, food delivery platforms should prioritise building user trust through transparent and consistent AI recommendation systems, enhance decision ease through intuitive interfaces, and manage cognitive load by limiting the number of recommendations and presenting information clearly. Platforms should shift from purely relevance-driven strategies to experience-driven personalisation that emphasises trustworthiness and cognitive efficiency.

Future research may extend this framework to other digital service platforms, adopt longitudinal designs to track behavioural changes over time, explore additional variables such as perceived usefulness and algorithm transparency, and conduct cross-cultural comparisons to understand how cultural factors moderate these relationships.

7. Limitations and Future Scope of the Study

This study has certain limitations that should be considered while interpreting the findings. The research was conducted with only 200 respondents, most of whom were young students aged 21-25, which may limit the generalisability of the results to all users of food delivery applications. The study focused only on users of Swiggy and Zomato, restricting the applicability of the findings to other platforms and industries. Since the data was collected at a single point in time through self-reported questionnaires, the responses may contain personal bias and may not reflect long-term behavioural changes. Additionally, the study examined only selected variables such as trust in AI recommendations, perceived relevance, perceived decision ease, and cognitive load, while excluding other important factors like privacy concerns, perceived usefulness, and algorithm transparency.

Future research can address these limitations by using larger and more diverse samples from different demographic groups and geographical regions. Studies may also compare different digital platforms and service industries to understand consumer behaviour in various contexts better.

Longitudinal research can help examine changes in user perceptions and behaviour over time. Furthermore, future studies can include additional variables such as customer satisfaction, loyalty, privacy concerns, and transparency of AI systems to provide a more comprehensive understanding of AI-driven hyper-personalisation and its impact on consumer usage behaviour.

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