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Consumer Acceptance Of The Use Of Artificial Intelligence In Online Food Delivery Service: Evidence From Delhi/Ncr

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Abstract
Artificial Intelligence (AI) has emerged as a disruptive innovation, accelerating digital transformation and reshaping food ordering and delivery systems. This study explores the predictors of consumers' intention to adopt AI-driven online food delivery services (AIOFDS), extending the Technology Readiness and Acceptance Model by incorporating AI-specific constructs such as customization and interactivity. AI-powered features—chatbots, recommendation engines, image recognition, and personalized checkout—enhance user experiences and streamline processes. Data were collected from 587 respondents in Delhi/NCR through convenient sampling (Jan–Mar 2024) and analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM) to assess measurement and structural models. Findings indicate that insecurity negatively influences perceived usefulness, while discomfort reduces ordering intention. Conversely, innovativeness, perceived ease of use, perceived usefulness, customization, and interactivity significantly predict ordering intention. The study provides both academic and managerial implications, highlighting how businesses can leverage AI-based features to design effective strategies, improve customer engagement, and enhance competitiveness in the retail and technology-driven marketplace.

Keywords: TRAM, PLS-SEM, customization, interactivity, Vedic Mathematics, Artificial Intelligence Based Online food delivery service.

1. Introduction

AI is a crucial innovation that has increased digital transformation across industries, particularly over the past decade (Dwivedi et al., 2019). In today's digital era, technological advancements have significantly transformed the business landscape, with artificial intelligence (AI) playing a key role in this shift (C. Wang et al., 2023). AI enhances consumer engagement by creating interactive experiences, increasing their willingness to share personal information (Kronemann et al., 2023). AI technologies have accelerated the shift from conventional ordering over the phone toadvanced "online platforms", transforming the waymeal business involves interactions between restaurants, customers, and delivery services(Can Saygıner, 2024). Application in the food industry plays significant role in enhancing customer convenience and company growth. AI-driven customer solutions include chatbots, recommendation engine, image recognition, personalized experiences, and streamlined checkout processes (D. Lim et al., 2023). Online food delivery services have particularly benefited from AI, that allowing them to operate more efficiently and methodically (Mayank Goyal et al., 2023). AI revolutionsed the industry by offering tailored suggestion based on order history, browsing behavior, and dietary requirement. AI-driven search features that make it easier to find particular meal/dish, also it helps to adjusts pricing strategy in real time based on demand, weather, and peak hours, ensuring fair pricing for both customers and restaurants. AI also optimizes delivery routes by analyzing traffic patterns, delivery distances, and driver availability, which leads to faster and fresher deliveries. The Indian online food delivery market is expected to bring revenue of "$43.78 billion in 2024", with an anticipated "annual growth rate (CAGR 2024–2029) of 15.98%" (Statista, 2024).

Majority of current research provides generalized observations without taking into account the effects of AI-driven elements like real-time surveillance, tailored feedbacks, &**"**automated customer interaction". The research examines the shifts in "AI-driven**"** online ways for delivering meals in the developing "market". While numerous studies have examined AI's role in the e-commerce industry, primarily from standpoint of technology experts **("**Liu et al., 2022"**)**, research specifically focused on AI based online food delivery applications remains limited. Experts in AI adoption (Belanche et al., 2020) have identified **"Technology Readiness Index (TRI)"** as relevant yet underutilized structure in this domain. To bridgethis gap in the study, this study integrates **"TRI"** with **"Technology Acceptance Model (TAM)"**in order to investigate intents of the clientregarding the use of AI-based food delivery applications. **"The Technology Readiness and Acceptance Model"** is employed to develop a conceptual framework that AI-specific constructs in order to answer the research question. This framework is empirically tested using survey data collected from 587 customers. The study begins with a literature review to establish the theoretical groundwork, followed by hypothesis development. After that, it goes under details for research methodology, including sampling techniques, data collection method, and the design of the research instrument. The findings are analyzed and presented, leading to a discussion on managerial and theoretical implications. The final section addresses the study's limitations, outlines future research directions, and finally, study end with the discussion, conclusion& contribution of the study. The primary aim of this study is to assess how AI has enhanced online food delivery applications and to identify key features that can further improve their effectiveness.

2. Artificial intelligence in Online food delivery application

Online food delivery services (OFDS) are online platforms that allow customers to order meals through mobile application from partner restaurants (Ray et al., 2019). Personalized is one of the most significant uses of AI in food delivery. To provide personalization recommendation, AI algorithms analyze user data, such as browsing history, purchasing behavior, and preferences, This personalization feature in OFD platform not only improve customer satisfaction and retention but also boost sales (Chen & Biswas, 2021). AI also leverages location-based recommendations to recommend nearby restaurants and popular cuisines, helping users to find new dining options and increasing engagement with food delivery apps. Furthermore, AI improves user experiences through chatbots and voice assistants, which assist with customer enquiries, navigation, and order placement, providing instant support (Leung & Wen, 2020).As Infolks (2021) points out, visual recognition technology makes ordering even easier by allowing user to get recommendation on the uploaded images of dishes over website/app that make user experience more interactive and convenient

3. Theoretical framework and hypotheses development

Technology readiness and adoption are crucial research topics in today's technology-advance landscape. The Technology Acceptance Model (TAM) (Davis, 1989) is widely used to examine technology adoption, while Technology Readiness (TR) represents a customer's willingness to embrace tech**"(**Parasuraman, 2000)".

I. "TR (Technology Readiness)"

Technology Readiness (TR) refers to a person'sinclination to embrace &make use of new technologyto achieve personal and professional goals. It can be understood as "an overall state of mind shaped by a combination of mental enablers and inhibitors that collectively influence a person's willingness to adopt new technologies" (Parasuraman, 2000, p. 308).The Technology Readiness Index (TRI) comprises four key dimensions, categorized into two groups:

II. TAM (Technology Adoption Model)

Technology Acceptance Model (TAM) is popular and well recognized framework for studying consumer intention to use new technology. According to Davis (1989), a user's intention to adopttwo important things influence technology:Perceived Utility (PU).
Research has demonstrated that TRAM enhances the applicability of both models in marketing contexts. The TRAM model has been widely applied in studies on new technology adoption across various domains, including; Mobile payments (Martens et al., 2017; Shin & Lee, 2014);Social media adoption (Jin, 2013);Digital services in B2B healthcare (Hallikainen & Laukkanen, 2016);Mobile electronic medical records (Kuo, Kiu, & Chen-Chuang, 2013); : E-service systems (Lin et al., 2007);Augmented Reality Open banking **("Sivathanu, 2019")**; (AR) in tourism **("Chung et al., 2015");** Services for self-checkout in supermarkets that sell groceries in retail **("Mukerjee et al., 2019").**

Context-Specific Variables

- **Customization (CST)**

Customization (CST) refers to a retailer's ability to provide transactional customization to consumers (Srinivasan et al., 2002). In the context of e-commerce, CST is defined as a website's ability to adapt to customer needs automatically or allow user to modify it to suit their preferences (Lee &Benbasat, 2004). As per the study of (Piller & Müller, 2004) , many customers using online food delivery apps prefer to customize their meals based on personal tastes rather than choosing standardized optionsCST allow user to customize food with ease using AI-powered technology (Pierdicca et al., 2015; Kahn et al., 2018; Chopra, 2019).is recognized as a major advantage of e-commerce and mobile commerce (m-commerce) (Morosan, 2014; Chong et al., 2012). AI-driven online food delivery services (AIOFDS) increase user satisfaction by offering customization meal suggestions, ensuring a more personalized and engaging ordering experience.

- **Interactivity (INT)**

Interactivity (INY) is defined as "the extent to which users can participate in modifying the form and content of a mediated environment in real-time". The degree of involvement customer feels when they interact with the seller is reflects how customer perceive involved.(Thamizhvanan, 2013). AI Based Online Food Delivery Service (AIOFDS) technologies improves interactivity by providing customers with real-time instruction on product locations, usage, discounts, pricing, and availability via mobile applications&notifications **("Kimberly, 2016")**. AI-driven Online food delivery service. Consequently, the highly interactive nature of AIOFDS is expected to significantly influence consumer shopping behavior, making AI-driven.Several researchers have explored AI-based online food delivery services. Saygıner et al. (2024) examined Food distribution systems powered by AI during and after COVID-19, Dr. Rashmi et al. (2022) studied AI in online food delivery, and Nunkoo et al. (2024) focused on AI-driven drone food delivery services. However, we utilized the TRAM model to predict consumer intention toward AI-based online food delivery services in India, an area that remains largely unexplored.

4. Hypotheses Development

This study develops a conceptual model by integrating the Technology Readiness and Acceptance Model (TRAM) with two variables unique to the context toanalyze people intentions to order from AIOFDS in India. Following the TRAM framework, the research explores how OPT, INNOV, DIF, and INS impact PU and PEOU, and subsequently examines the effect of PEOU on PU. Additionally, the study investigates the influence of PEOU, PU, CST, and INY on shopping intention at AIOFDS. The proposed theoretical model as depicted in Image.

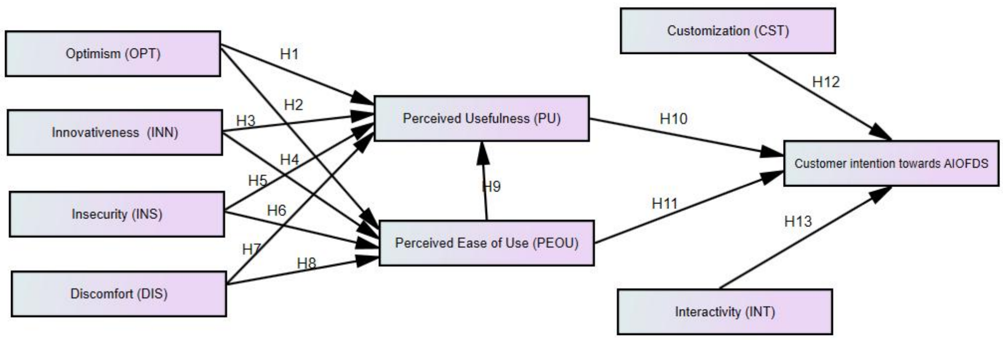

Figure 1. Conceptual Model of Customer Intention Towards AIOFDS

Optimism and Perceived Usefulness

Technological optimism is known as"a positive view of technology and a belief that it offers people increased control, flexibility, and efficiency in their lives"**(“Parasuraman & Colby, 2015, p. 60”)**. This idea also applies to artificial intelligence **“(AI)”**, since individuals can view it as either "heaven" or "hell"**(“Kaplan & Haenlein, 2020”)**.Consequently, optimistic people are more likely to embrace new technologies (Chen & Lin,2018). Lundberg’s (2017) study on the self-service technology adoption, discovered thatperceived usefulness is strongly influenced by optimism Thus, we propose the following hypothesis.
H1: Optimism positively affects the perceived usefulness of ordering food at AIOFDS.

Optimism and Perceived ease of use

Optimism (OPT) reflects an individual's positive outlook on technology, believing that it enhances adaptability, efficiency and authority. It represents a person's inclination to embrace new technologyas they arrive in the market. Studies indicate that OPT influences **“perceived ease of use (PEOU)”**, a study involving 123 employees in Norway found that OPT significantly influenced PEOU in the adoption of a system for electronic health records (Godoe & Johansen, 2012).. Thus, we propose the following hypothesis.
H2: Optimisim positively affects the Perceived ease of use of ordering food at AIPARS.

Innovativeness and Perceived Usefulness

Innovativeness (INN) refers to the process of developing new technologies or enhancing existing ones to meet evolving consumer needs (Rahmania et al., 2023). Research on technology adoption presents mixed findings regarding the relationship between INN and perceived usefulness (PU). Some studies, such as those on mobile payment adoption and health apps, found no significant association between INN and PU. However, other research on new technology acceptance confirms that INN positively influences PU (Kim & Chiu, 2019). Thus, following hypothesis is put forward.

H3: INNOV positively affects PU of Ordering food at AIOFDS.

Innovativeness and perceived ease of use

Innovativeness (INN) has been shown to positively influence perceived ease of use (PEOU) in consumer shopping intentions, particularly in retail stores that integrate artificial intelligence (AI) (Pillai et al., 2020). Additionally, research on AI-based recruitment systems has established a positive relationship between INN and perceived usefulness (PU) (Lee et al., 2021).Thus, the following hypothesis is proposed.

H4: INNOV positively affects PEOU of ordering activity at AIOFDS

Discomfort and Perceived Usefulness

Discomfort (DIF) is defined as the technological fear and apprehension consumers experience toward new technology. It reflects the negative emotions and resistance individuals may feel when confronted with emerging technologies (Cambre & Cook, 2005)..In the case of AI-powered online food delivery services (AIOFDS), automation plays a crucial role in enhancing user convenience by providing features such as meal and restaurant discovery, online images, order tracking, and location accessibility. Thus, we put forward the following hypothesis.

H5: DIF negatively affects PU to ordering activity at AIOFDS.

Discomfort and Perceived ease of use

Discomfort (DIF), where people experience to have discomfort, are less likely to embrace and use new technology, because they have negative opinion on them (Blut & Wang, 2020).In the context of AI-powered online food delivery services (AIOFDS), advanced features such as food ordering, restaurant search, availability tracking, and real-time order monitoring may overwhelm some consumers, making them perceive the system as complex and difficult to navigate. Thus, we put forward the following hypothesis.

H6: DIF negatively affects PEOU to ordering activitiy at AIOFDS.

Insecurity and Perceived Usefulness

Consumers who experience insecurity (INS) tend to be less reliant on technology, fearing that it may fail at critical moments, INS is recognized as a key factor contributing to lower technology adoption (Tsikriktsis, 2004). Existing research indicates that INS adversely affects **"perceived usefulness (PU)"**of novel tech. However, some researchsuggestsno significant relationship between INS and PU.SinceAIOFDS is entirely technology-driven, consumers may feel uncertain or skeptical about its reliability, which could hinder their acceptance of the system. Therefore, a hypothesis is proposed based on this premise.

H7: INS negatively affects PU to ordering activitiy at AIOFDS.

Insecurity and Perceived ease of use

Insecurity (INS) reflects, people lack of confidence in embracing new technology. It has been demonstrated to impede technology adoption (Parasuraman & Colby, 2001) and act as a negative and deterrent factor for technological preparedness**("Kuo et al., 2013").**According to studies, on theembracing novel tech,suggests that INS negatively impacts perceived ease of use (PEOU) (Kim & Chiu, 2019; Martens et al., 2017). However, some research suggests that no significant relationship between INS and PEOU.When utilizing technology-driven service, some consumers lack confidence may experience uncertainty and hesitant (Godoe& Johansen, 2012 Thus, a hypothesis is formulated accordingly.

H8: INS negatively affects PEOU to ordering activitiy at AIOFDS.

Perceived ease of use and Perceived Usefulness

Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) are key determinants of technology adoption. Research on new technology adoption has consistently examined the relationship between PEOU and PU. However, some studies, such as the acceptance of AR applications, have found no significant relationship between PEOU and PU (Rese et al., 2017).As AIOFDS is a fully automated, AI-powered store, its effortless ordering process and AI-driven assistance are expected to enhance its perceived usefulness. Therefore, the followingexamination is proposed.

H9: PEOU positively influences the PU of ordering activities at AIOFDS.

Perceived ease of use and Intention to use

Customer intention to order food at AIOFDS reflects the subjective likelihood of a consumer's involvement in a specific shopping behavior. Perceived Ease of Use (PEOU) is a key factor in technology acceptance (Davis, 1989).Research on M-commerce adoption has shown that PEOU influences the intention to adopt. Studies in technology acceptance also indicate that PEOU affects usage intention. Thus, the following theory is put forth.

H10: PEOU positively influences the Customer intention to online ordering at AIOFDS.

Perceived Usefulness and Intention to use

When customers perceive that technology enhances their performance and efficiency, they are more likely to accept and adopt it (Davis, 1989). Perceived Usefulness (PU) has been shown to influence e-shopping usage and mobile shopping behavior. Additionally, PU drives the adoption of smart products (Mani &Chouk, 2018).Studies on new technology adoption further confirm the impact of PU on behavioral intention. Consequently, consumers may perceive shopping at AIOFDS as highly useful, leading to the following hypothesis.

H11: PU positively influences the customer intention to online ordering at AIOFDS.

Customization and Intention to use

Customization (CST) refers to the extent which a companytailors its services to meet diverserequirements of clients. This is a key determinant of customer behavior when purchasing online, m-commerce, &retail malls. At AIOFDS, AI-powered mobile apps and digital signboards provide personalized food recommendations and exclusive deals, which may shape customers' intention to order online. Consequently, the following theory is put forth.

H12: CST positively influences the customer intention to online ordering at AIOFDS.

Interactivity and Intention to use

Interactivity (INT) plays a crucial role in facilitating customer-business interactions (Srinivasan et al., 2002; Ballantine, 2005) and serves as a key predictor of consumer behavior in smart retail environments. At AIOFDS, AI-powered technology fosters a highly interactive experience by assisting customers in finding restaurants, checking availability, tracking orders, and making automated payments. Based on this, the following hypothesis is suggested.

H13: INY positively influences the customer intention at AIOFDS.

5. Method of Research

This section explains the survey tool and the data collection procedure. Primary studies are deployed in this study.

5.1 Research Survey Instrument Design:

This research employs a qualitative analysis approach, drawing insights from historical studies, literature, and documented evidence. To examine customer readiness and acceptance of technology will deploy quantative analysis, measurement scale was created using theliterature on **"Technology Readiness**" (TR) &technology adoption (Parasuraman, 2000). The scales used for INT **("Srinivasan et al., 2002")** & CST ("**Shao 2009"; "Kalinic & Marinkovic, 2016"**) were modifiedfor this study. Before gathering of data, six subject-matter experts in AI from academia were consulted to review the interview questionnaire. Using a five-point Likert scale,measurelatent variables that have been operationalized. To assess data reliability and internal consistency, Cronbach's alpha was applied. Following satisfactory pilot study results, primary data collection commenced. The constructs that have been operationalized aredetailed **in "Table I"**.

Table I. "Measurement Model Summary"

Constructs	**Items**	**Indicators**	**Sources**
Optimism (OPT)	OPT1	New technologies like AIOFDS contribute to a better quality of life.	Parasuraman and Colby (2015) Parasuraman (2000)
	OPT2	Technology like AIOFDS gives me more freedom to ordering food.	
	OPT3	Technology like AIOFDS makes me more efficient in my ordering food.	
	OPT4	I like the idea of using new technology like AIOFDS in ordering food.	
Innovativeness(INNOV)	INNOV1	In general, I am among the first in my circle of	Parasuraman and Colby (2015) Parasuraman

		friends, to acquire new technology like AIOFDS when it appears.	(2000)
	INNOV2	I can usually figure out new high-tech in using online food ordering like AIOFDS without help from others.	
	INNOV3	I keep up with the latest AIOFDS technological developments in my areas of interest	
	INNOV4	I prefer to use the most advanced technology like AIOFDS.	
Insecurity(INS)	INS1	Excessive use of technology like AIOFDS distracts people to a point that is harmful.	Parasuraman and Colby (2015) Parasuraman (2000)
	INS2	I am worried that while ordering food at AIOFDS, Someone will misuse my data which is provided by me while ordering.	
	INS3	When I have to only order at AIOFDS; I do not feel confident.	
	INS4	I do not consider it safe to provide personal information over the technology based app like AIOFDS.	
	INS5	Any online ordering service, like AIOFDS based business	

		transaction I do electronically should be confirmed later with a separate communication	
Discomfort	DIS1	I feel that new online technology in ordering food and AIOFDS is not designed properly which can be understood by any individual person.	Parasuraman and Colby (2015) Parasuraman (2000)
	DIS2	New technologies like AIOFDS, have health or safety risks that are not discovered until after people have used them	
	DIS3	There should be caution in replacing important people tasks with technology because new technology like AIOFDS can break down or get disconnected	
	DIS4	I feel that Technology used at AIOFDS would always fail at the worst expected time.	
Perceived Usefulness(PU)	PU1	Online ordering food technology like AIOFDS helps me to learn more efficiently	Davis (1989)
	PU2	Online ordering food technology like AIOFDS improves my academic	

		performance	
	PU3	Online ordering food technology like AIOFDS makes my learning more effective.	
	PU4	Online ordering food technology like AIOFDS makes it easier to learn	
	PU5	Overall, Online ordering food technology like AIOFDS is beneficial for my learning	
Perceived ease of use(PEOU)	PEOU1	Learning to use Online ordering food technology like AIOFDS is easy for me	Davis (1989)
	PEOU2	It is easy to get food service from online ordering food technology like AIOFDS	
	PEOU3	The process of using Online ordering food technology like AIOFDS is clear and understandable	
	PEOU4	It is easy for me to become skilful at using Online ordering food technology like AIOFDS	
	PEOU5	Overall, I find Online ordering food technology like AIOFDS is easy to use	
Customization (CST)	CST1	AIOFDS would provide purchase suggestions which suit my	(Kalinic and Marinkovic, 2016; Shao et al., 2009)

		requirements.	
	CST2	AIOFDS would enable me to order food that are suitable for me.	
	CST3	The promotions and advertisement that AIOFDS provide me are perfectly suitable as per my food ordering requirement.	
	CST4	AIOFDS would make me experience like a unique customer.	
	CST5	I am confident that AIOFDS would be customized as per my requirement.	
Interactivity (INY)	INT1	AIOFDS would enable me to see the food from different angles.	(Ballantine, 2005; Srinivasan et al., 2002)
	INT2	AIOFDS would have search tools that enable me to locate food.	
	INT3	AIOFDS have tools that make food comparisons easy.	
	INT4	Shopping at AIOFDS is very engaging.	
	INT5	Shopping at AIOFDS is very dynamic.	
Customer intention towards AIOFDS	OI1	I will use Online ordering food technology like AIOFDS on a regular basis in the future	Davis(1989)
	OI2	I will frequently use Online ordering food	

		technology like AIOFDS service in future.	
	OI3	I intend to use Online ordering food technology like AIOFDS to assist my learning	
	OI4	Assuming I had access to Online ordering food technology like AIOFDS , I would use it	

5.2 Sampling and Data Collection

For primary data collection, a structured questionnaire (Table I) was administered to respondents. The survey was conducted in Delhi/NCR, recognized as a prominent food hub in India. The target participants were individuals who actively used online food delivery services. A convenience sampling method was employed to survey consumers who used online food delivery services in Delhi/NCR. To minimize bias, data collection took place at various times and on different days. The process spanned three months, resulting in 587 fully completed and valid questionnaires for analysis.

Four sections make up the questionnaire. Section 1 collected the respondents' demographic data, including name, gender, age, level of education, occupation &frequency of using online food delivery app. Section 2 includes five points. Likert scale inquiries to gauge thebehavioural intention towards using online food delivery service. By employing a quantitative method, this examination identifies the elements that influence theimplementation of artificial intelligence technology in digitalfood delivery service in Delhi/NCR. Table 1 displays items and constructs modified to assess theintention of consumer. The operationalized constructs are detailed in Table II. Respondents were contacted via phone and email &made aware ofto completequestionnaire. The information gathered was analyzed utilizing (SPSS) and Smart-PLS.

6. Results

6.1 Data Analysis and Results

Table II presents the demographic insights of the respondents.

Table II. Demographic profile of the respondents

Demographic	**Characteristics**	**Frequency**	**Percentage**
Gender	Male	363	61.8%
	Female	224	38.2%
Age	Below 18 years	108	18.39%
	18-24years	146	24.87%
	25-34 years	208	35.43%
	35-44 years	64	10.90%
	45-54 years	43	0.73%
	Above 55 years	18	0.30%

Education Level	Secondary School	53	0.90%
	Sr. Secondary School	27	0.45%
	Under-Graduate	23	0.39%
	Graduate	251	42.7%
	Post-Graduate	228	38.8%
	Ph.D	5	0.08%
Personal Income in INR(Monthly)	Below 10,000	121	20.61%
	10,000-50,000	63	10.73%
	50,000-1,00,000	81	13.79%
	1,00,000-1,50,000	214	36.45%
	1,50,000 and above	108	18.39%
Frequency of Using Online Food Delivery Services	Daily	103	17.54%
	Weekly	273	46.50%
	Fortnighlty	118	20.10%
	Monthly	93	15.84%
Prior experience of using technology for ordering food.	More than 6 months More than 1 year	390 197	66.4% 33.56%

6.2 "Reliability and validity analysis of the items"
A reliability analysis was carried out to evaluate the items of each construct for internal validity and consistency. All items' Cronbach's α was tenable because it was more than 0.7, in social science research, this is advised **("Nunnally, 1978")**. Composite reliability, also known as construct reliability, is a metric for internal consistency in scale items, much like Cronbach's alpha (Netemeyer et al., 2003).It's an"indicator of the shared variance among the observed variables used as an indicator of a latent construct" **("Fornell and Larcker, 1981")**.

6.3 "Hypothesis Testing"
Table III. Validity and Reliability for all Constructs.

Measurement Items	Loadings	Α	CR	AVE
Optimism	**0.916**	**0.936**	**0.955**	**0.840**
OPT1	0.888			
OPT2	0.937			
OPT3	0.896			
OPT4	0.944			
Innovativeness	**0.902**	**0.925**	**0.946**	**0.816**

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INNOV1	0.870			
INNOV2	0.938			
INNOV3	0.865			
INNOV4	0.937			
Insecurity	**0.993**	**0.995**	**0.995**	**0.978**
INS1	0.994			
INS2	0.894			
INS3	0.990			
INS4	0.982			
INS5	0.985			
Discomfort	**0.997**	**0.998**	**0.998**	**0.994**
DIS1	0.997			
DIS2	0.996			
DIS3	0.997			
DIS4	0.998			
Perceived Usefulness	**0.705**	**0.858**	**0.904**	**0.703**
PU1	0.788			
PU2	0.177			
PU3	0.881			
PU4	0.783			
PU5	0.899			
Perceived Ease of Use	**0.845**	**0.902**	**0.926**	**0.715**
PEOUI	0.799			
PEOU2	0.896			
PEOU3	0.835			
PEOU4	0.888			
PEOU5	0.807			
Customization	**0.807**	**0.935**	**0.955**	**0.841**
CST1	0.948			
CST2	0.805			
CST3	0.953			
CST4	0.381			
CST5	0.953			
Interactivity	**0.850**	**0.907**	**0.929**	**0.724**
INT1	0.818			
INT2	0.885			
INT3	0.831			
INT4	0.888			
INT5	0.831			

Ordering Intention	**0.778**	**0.791**	**0.863**	**0.616**
OIN1	0.840			
OIN2	0.616			
OIN3	0.884			
OIN4	0.774			

6.4 "PLS-SEM"

PLS-SEM is employed in studies when the research purpose is the extension of the present theory (Hair et al., 2011). PLS-SEM has also been employed in several technology adoption studies for online behavior. Hence, the data analysis was done employing the Smart PLS 4.0.All Outer loadings value of items which is above the 0.7 except PU2 (0.177) and CST4 (0.381) which is below the threshold value, so we remove these two item PU2 and CST4 for analysis. The items displayed high internal consistency, with Cronbach's alpha values greater than 0.7. As shown in Table II, the CR values further validate strong reliability and internal consistency, with all item loadings surpassing the 0.6 threshold. Additionally, the AVE values exceeded the 0.5 benchmark, confirming the convergent validity of all constructs.

The discriminant validity of the constructs is established by comparing their inter-correlationsusing the off-diagonal values of the AVE, as shown in **"Table IV"**.

Table IV. Discriminant Validity

Research Construct	**OIN**	**CST**	**DIF**	**INNOV**	**INS**	**INT**	**OPT**	**PEOU**	**PU**
OIN	0.785								
CST	0.749	0.917							
DIF	0.01	0.07	0.997						
INNOV	0.573	0.739	-0.054	0.903					
INS	-0.115	-0.073	-0.005	-0.077	0.989				
INT	0.636	0.628	-0.096	0.637	-0.158	0.851			
OPT	0.699	0.865	0.038	0.706	-0.097	0.684	0.917		
PEOU	0.719	0.823	0.078	0.646	-0.07	0.584	0.806	0.876	
PU	0.723	0.878	0.021	0.725	-0.107	0.648	0.804	0.844	0.839

Table VI: The result of VIF, R^2, F^2, and Q^2

	VIF			**R^2**	**F^2**			**Q^2**
	OIN	PEOU	PU		OIN	PEOU	PU	
OIN				0.752				0.385
CST	8.221				0.074			
DIF		1.015	1.026			0.011	0.002	
INNOV		2.018	2.098			0.039	0.125	
INS		1.01	1.01			0.000	0.006	
INT	1.78				0.088			

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OPT		2.022				0.705	0.042	
PEOU	7.759			0.664	0.228		0.666	0.649
PU	5.375			0.817	0.158			0.685

Statistics on multi-collinearity reveal how the independent variables are correlated with one another. All of the constructs have VIF values below 10, as Table 6 demonstrates(Robert, 2007),showing that the model has no multi-collinearity problems. OPT (O.705) has largest effect size on PEOU & PEOU (0.666) has largest effect size on PU with f^2 value. PEOU (0.228) & PU (0.158) has medium effect size on OIN. finally, DIF, INNOV, INS, has small effect on PEOU with f^2 value, respectively are; 0.011,0.039. 0.000. INT (0.088) has smallest effect size on OIN. DIF, INNOV, INS, OPT has small effect size on PU; 0.002, 0.125. 0.006, 0.042 respectively. Table 8's valid path coefficient has a p-value of less than 0.05.

A model's predictive usefulness is determined by its Q square value. A model's Q square value needs to be higher than zero for a quantitative analysis based on primary data.Additionally, Table 7 showed that every Q2 value is greater than 0(Q^2 OIN= 0.385, Q^2 PEOU=0.649; &Q^2 PU=0.685).

A model's R square indicates the amount of variance in the dependent variabledue to the independent variables which are present in the model [M.lewis,2003]. Table 8 shows that The OIN, PEOU, and PU have been explained by 75.2%, 66.4%, and 81.7% by the change of independent variables.

6.4.2 Structural Model

Path analysis was carried out following validation of the measurement model's validity and reliabilityusing structural framework to evaluate relationships between constructs, as illustrated Figure II. shows the route coefficients as well astheir important levels are detailed in Table V.

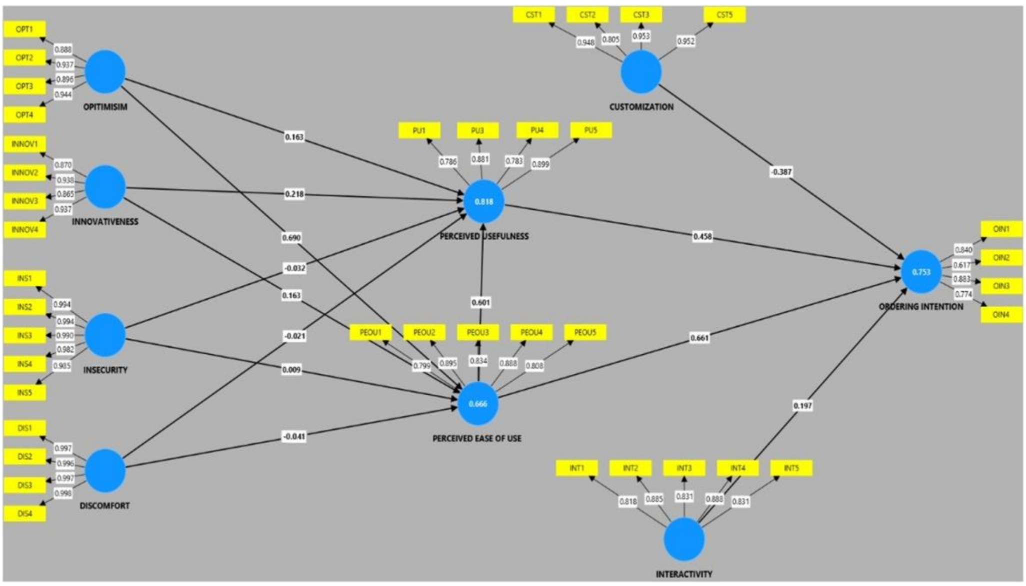

Figure II. Conceptual Model of Customer Intention to order at AIOFDS

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Table VII. Path Coefficients

Hypothesis	Path	Path Coefficient	T Statistics	P value	Decision
H1	Optimisim-> Perceived Ease Of Use	0.163	10.997	0.000	Supported
H2	Optimisim-> Perceived Usefulness	0.690	2.170	0.003	Supported
H3	Innovativeness-> Perceived Ease Of Use	0.163	2.190	0.029	Supported
H4	Innovativeness-> Perceived Usefulness	0.218	5.139	0.000	Supported
H5	Insecurity -> Perceived Ease Of Use	0.009	0.251	0.802	Not supported
H6	Insecurity -> Perceived Usefulness	-0.032	2.022	0.043	Supported
H7	Discomfort-> Perceived Ease Of Use	-0.041	1.214	0.197	Not Supported
H8	Discomfort-> Perceived Usefulness	-0.021	1.334	0.182	Not Supported
H9	Customization->Ordering Intention Towards AIOFDS	0.145	2.675	0.007	Supported
H10	Interactivity-> Ordering Intention Towards AIOFDS	0.058	3.403	0.001	Supported
H11	Perceived Usefulness -> Customer Intention Towards AIOFDS	0.120	3.822	0.000	Supported
H12	Perceived Ease Of Use ->Perceived Usefulness	0.085	7.075	0.000	Supported

H13	Perceived Ease Of Use -> Customer Intention Towards AIOFDS	0.148	4.461	0.000	Supported

The findings reveal that optimism (OPT) significantly affects perceived utility (PU) (β=0.75, $p<0.01$) &"perceived ease of use (PEOU)" (β=0.063, $p<0.05$) in the context of AIOFDS, contradicting previous research by Kumar and Mukherjee (2013). Customers exhibit optimism regarding the ease of use and usefulness of AIOFDS, as they are already familiar with using technology for online food ordering. Innovation (INN) favourably affectsboth **"PEOU"** (β=0.074, $p<0.05$) &**"PU"** (β=0.042, $p<0.05$), indicating that customers with a creative perspectiveAIOFDS tech as both user-friendly and beneficial for ordering food. However, discomfort (DIF) does not significantly impact PEOU (β=-0.021, ns) or PU (β=-0.041, ns), aligning with studies on self-service technology. Since customers are accustomed to using online food delivery apps, discomfort does not hinder their perception of ease of use or usefulness. Insecurity **("INS")**doesn'tnegativelyimpactPEOU (β=0.038, ns) but has a positive impact on PU (β=-0.016, $p<0.01$), indicating that security concerns influence customers' perception of AIOFDS's usefulness. PEOU significantly enhances PU (β=0.085, $p<0.001$), while both PEOU (β=0.148, $p<0.001$) and PU (β=0.120, $p<0.01$) significantly affectbehavioralintentto order food via AIOFDS, demonstrating that customers are inclined to use the service. Additionally, customer satisfaction (CST) strongly influences online intention (OIN) (β=0.35, $p<0.001$), reinforcing its significance in shaping customer behavior.At AIOFDS, there are offered more customized food to customer due to AI based technologies. INT influences positively to OIN (β=0.058, $p<0.001$) which conveys that due to AIOFDS technologies, interactivity is high. Hence INT positively influences OIN.

7. Discussion

The findings of Customer intention to ordering food in AIOFDS, indicate that optimism (OPT) influences both perceived ease of use (PEOU) and perceived usefulness (PU), as consumers are confident in adopting new technology for food ordering (Ali et al., 2015). Innovation (INN) also positively affects PEOU and PU, as customers who frequently order food tend to be technologically aware, interested in emerging trends, and quick to adapt to new systems like AIOFDS. Discomfort has a negative impact on PEOU and PU; however, its effect is not significant, as most customers are already familiar with using technology for shopping, contradicting findings from studies on self-service technology. While insecurity does not influence PEOU, it does affect PU when ordering through AIOFDS. Consumers value human interaction when ordering food, which is absent in AIOFDS. As a result, INS do not impact PEOU but has a significant effect on PU.

The study confirms that PEOU has a significant impact on PU, consistent with previous research (Natarajan et al., 2017). This suggests that when consumers find AIOFDS easy to use, they are more likely to perceive it as beneficial. Both PEOU and PFL positively influence the intention to order food through AIOFDS. Customization (CST) plays a crucial role in shaping online ordering intention (OIN) at AIOFDS (Liébana-Cabanillas et al., 2017). CST is widely recognized as a key benefit of e-commerce and mobile commerce, enabling seamless food ordering through AI-powered platforms. Interactivity (INT) also significantly impacts OIN at AIOFDS Similar technologies are incorporated into AIOFDS, research has highlighted the significance of interactivity in AI-driven experiences, particularly in virtual reality settings.

8. Conclusion

The purpose of this investigation was toshed light on consumer acceptancebehavior regarding AIOFDS inBharat. The research model was developed based on prior studies on IT adoption (Davis, 1989) and incorporated two context-specific factors, CST and INT, in relation to AIOFDS and framework was tested using the PLS-SEM method, effectively explaining the behavioral intention to order through AIOFDS.

OPT influences PEOU and impact PU, as consumers adopt AIOFDS for its convenience, control, and efficiency in food ordering. However, concerns related to INS persist, affecting PU but not PEOU, which contradicts previous research. Similarly, DIF does not impact either PEOU or PU, indicating buyers don'texperience unease with tech, whichcontrasts with findings from studieson tech for self-service. PEOU &PU are key forecasters ofOIN at AIOFDS. Additionally, the study highlights that context-specific factors, CST and INT, significantly influence OIN, aligning with existing research. The findings suggest that consumers are inclined to adopt AIOFDS based on these factors, though security concerns remain a challenge.This study contributes a model for understanding OIN at AIOFDS by integrating two context-specific variables into the TRAM framework.This study highlights the critical need for additional research on consumer behavior in AIOFDS and the adoption of technology to automate online food ordering systems in the food industry and encourages further interdisciplinary research to practically validate and apply these techniques.

9. Limitations and Future Research Lines

The study serves as an initial step in understanding customer behavioral intentions toward ordering from AIOFDS. However, certain limitations exist. Firstly, as a cross-sectional study conducted exclusively in India, the findings are geographically constrained, and caution should be exercised when applying them to different contexts. Expanding this research to other developing nations with diverse cultural backgrounds could provide broader insights. Furthermore, demographic variables like gender, age, education, &income could be analyzed in a comparative framework. Future studies may incorporate additional variables, including “perceived risk”, “trust”, “customer enjoyment”“customer experience”,&“satisfaction”, once AIOFDS is operational in Bharat. Since tests were conducted on the model solely within Bhartiya market, presents opportunities for additionalresearch in other emerging economies. The conceptual framework, while theoretically promising, has yet to be tested in real-world scenarios.

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