Accountancy Business and the Public Interest
ISSN: 1745-7718

Volume: 40
Issue Number:10

IMPACT OF NETWORK EXTERNALITIES ON USE BEHAVIOUR OF ONLINE GROCERY SHOPPING APPLICATIONS

CHINMAY BAXI[1], KRUNAL MEHTA[2], ANUSHREE KARANI MEHTA[3], RASANANDA PANDA[4] and DIVYAND PUROHIT[5]

[1]Associate Professor, P.P. Savani University, Surat, Gujarat, India 394125. Email: chinmay.baxi@ppsu.ac.in
[2]Assistant Professor, Shanti Business School, Ahmedabad, Gujarat, India 380058.
Email: mkrunal93@gmail.com
[3]Assistant Professor, Shri Jairambhai Patel Institute of Business Management and Computer Applications, Gandhinagar, Gujarat, India 382007. Email: anushree.karani@gmail.com
[4]Professor, MICA Ahmedabad, India 380058. Email: rasananda.panda@micamail.in
[5]Assistant Professor, CHARUSAT Changa, India 388421

Abstract

Purpose- The main goal of this study is to explore how network externalities influence task technology fit for Online Grocery Store (OGS) smartphone applications by integrating the unified theory of acceptance and use of technology (UTAUT) and UTAUT2 framework and its impact on the behavioural intention and actual use behaviour.

Design/methodology/approach- In this study the data was collected from the 665 respondents and were tested by using PLS algorithm.

Findings- Results revealed that network externalities positively impacted task-technology fit. Further, task-technology fit impacted all the UTAUT constructs. But the behavioural intention was not impacted by performance expectancy, social influence, facilitating conditions, hedonic motivation and risk, and behavioural intention also lead to actual usage behaviour.

Originality/value- The study highlighted that how online retailers can understand the factors which lead to behavioural intention and actual use behaviour and how task-technology fit is impacting the various constructs to make application more user friendly.

1. INTRODUCTION

Online grocery shopping (OGS) has become increasingly popular as a result of the COVID-19 pandemic, and consumer behaviour has shifted in favor of this method (Roggeveen & Sethuraman, 2020). Global customer interest in online shopping has increased in recent years (Eriksson & Stenius, 2022). This is mostly because of contactless delivery, safe payment methods, flexible scheduling, and a large selection of products. Customers may shop whenever they want thanks to these conveniences, which saves them time and effort (McKinsey, 2020). Therefore, by allowing consumers to buy goods using their mobile devices, online grocery shopping (OGS) helps people to combine their personal and professional commitments (Liébana-Cabanillas et al., 2019).

According to Forbes (2020), online grocery sales in the United States increased from $1.2 billion in August 2019 to $7.2 billion by June 2020. Click-and-collect or home delivery was selected by 12% of European customers who started utilising new online grocery delivery services (McKinsey, 2020). Online grocery sales in India are predicted to rise from $3.95 billion in 2021 to $26.93 billion by 2027, representing an incredible 33% annual growth rate, according to Ecommerce (2023). The major forces behind this expansion include government programs that promote digital literacy and the digital economy, as well as increased internet accessibility and cheaply priced smartphones (Gupta & Kumar, 2023).

Most of the research on OGS, especially that done in the early 21st century, has been based on technology and psychology frameworks such as the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB). These studies (Ha & Harris, 2020; Roggeveen & Sethuraman, 2020) have looked into OGS from both an emotional and a technological standpoint. OGS's unique challenges in handling perishable goods set it apart from other e-commerce companies (Choudhary & Paul, 2019). Despite these obstacles, more companies are entering the market and investing in this rapidly growing sector of the economy. However, they still have difficulties with making a profit, building a devoted clientele, and allaying the concerns of clients who might be reluctant to make purchases online. For online grocery retailers to develop a devoted consumer base, they must understand what encourages and hinders online grocery shopping (OGS).

The majority of OGS research was done prior to the pandemic; thus, it would be helpful to examine how consumers are using OGS now that the epidemic has passed (Verhoef & Langerak, 2001; Van Droogenbroeck & Van Hove, 2017; Frank & Peschel, 2020). Though a lot of study has been done in the West, not much has been done when it comes to the online grocery sector in India. Through the integration of frameworks such as UTAUT and UTAUT2, recent research aimed to explore how network externalities affect the task-technology fit for OGS and how these aspects affect customer behaviour. In order to improve their offerings and adjust to evolving customer demands, online grocery stores should take into account the critical elements outlined in this study. The paper presents the theoretical framework, research methods, and study results. It then discusses the study's implications, limits, and recommendations for further research.

2. LITERATURE REVIEW AND DEVELOPMENT OF HYPOTHESIS

Using ideas from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), Task-Technology Fit (TTF), and Network Externalities (NE), the study examined consumers' intentions to engage in online grocery shopping (OGS). These OGS theories are discussed in the part that follows, along with a suggested model created to satisfy the goals of the investigation.

2.1 Network Externalities (NE)

In 1985, Katz and Shapiro introduced the notion of Network Externalities (NE). They clarified that a product or service's consumers stand to gain more if it has network externalities and has a sizable user base. "New externalities" (NE) is a phenomenon where a good or service becomes more valuable or beneficial as more people utilise it (Qasim & Abu-Shanab, 2016). Given that it sets the information and communication technology sector apart from other businesses, this idea is particularly pertinent to it (Cen & Li, 2020). Katz and Shapiro distinguished between two types of network externalities: direct and indirect.

The concept of a direct network externality posits that the value of a good or service increases with its user base. According to Sarkar and Khare (2019), those who use mobile shopping apps more frequently benefit from expanding their user base. As a result, there is a "network size effect," which states that the service is more beneficial with a larger customer base. Conversely, benefits from increased user numbers that result in enhanced or new services are referred to as indirect network externalities (Qasim & Abu-Shanab, 2016). For example, customers of a well-liked mobile shopping app might have access to additional services like booking travel or paying bills (Sarkar & Khare, 2019).

Both the user and the provider may take network externalities into consideration. Mostly from the user's point of view, this study looks at how consumers weigh a product or service's reach or scale before deciding to utilise it. Adoption decisions are frequently influenced by a product's current user count (Goolsbee & Klenow, 2002). According to a number of studies (Strader et al., 2007; Qasim & Abu-Shanab, 2016), network externalities can have a big impact on customer behaviour and willingness to utilise items or services.

2.2 Task-Technology Fit (TTF)

A theoretical framework known as the Task-Technology Fit (TTF) model was first presented by Goodhue and Thompson in 1995. It posits that users are more likely to adopt a technology if it meets their demands and makes it easier for them to do jobs efficiently. According to the TTF hypothesis, people are more likely to accept an information system if it increases productivity and seamlessly integrates with their jobs (Gebauer et al., 2010). TTF is especially important for online delivery apps, as customers may occasionally have to pick between various platforms when placing grocery orders.

Online grocery shopping systems (OGSs) allow clients to effortlessly obtain supplies from anywhere, even when they are by themselves. The TTF model highlights these benefits. By controlling contactless offline distribution, these systems also guarantee effective service (Zhao & Bacao, 2020). Zhao and Bacao (2020) looked at the factors impacting users' continuing use of online delivery apps using UTAUT and TTF. Task relevance, a crucial component of TTF, plays a significant role in influencing users' decision to use these services. As such, the TTF model is critical to the advancement of theoretical understanding. The hypothesis is as follows:

H1: Network externalities have a positive influence on task-technology fit.

2.3 Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) by integrating and analysing eight different perspectives on technology use. UTAUT focusses on four key areas to predict people's behavioural intentions about technology adoption: performance expectancy, effort expectancy, social influence, and facilitating factors. Venkatesh et al. (2003) claim that each of these elements has an impact on behavioural intention (BI). Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) was created by Venkatesh et al. (2012) to enhance the model's alignment with consumer technology adoption. This paradigm combines monetary value, habit, and hedonic motivation. To examine how people accept and use technology, the modified model has been empirically tested in consumer settings. UTAUT2 has been utilised in a number of research (Zhao & Bacao, 2020; Ain et al., 2016) to examine how users behave and use online platforms, such as online grocery applications.

Van Droogenbroeck & Van Hove (2021) extended the UTAUT2 model to include perceived risk, reported satisfaction of in-store purchases, felt time pressure, and innovativeness using online grocery shopping (OGS). Their results demonstrated how important perceived time constraints and inventiveness are in determining consumers' inclination to use online grocery delivery services. In an additional study conducted in Mauritius, consumer intentions towards OGS were investigated using the UTAUT2 model, which included perceived risk and perceived trust (Human et al., 2020). Interestingly, Mauritian customers' desire to use online grocery services was not significantly impacted by perceived risk, perceived trust, effort anticipation, or social influence (Human et al., 2020).

Many research have looked at the factors influencing customers' intentions to use OGS, but not many have developed a comprehensive paradigm that considers UTAUT2, Task-Technology

Fit (TTF), and network externalities. Although UTAUT2 is extensively employed in other sectors of the economy, its use in OGS is still very restricted, especially in developing nations. This is the first study to use TTF, network externalities, and UTAUT2 to examine OGS acceptance and use in India. The UTAUT model should be modified for different technologies and geographical areas, according to Venkatesh et al. (2003), and augmented with pertinent components. In accordance to that proposal, our study uses that approach, and Figure 1 illustrates the conceptual framework.

2.4 Behavioural Intention (BI) and Use Behaviour

It relates to a user's conscious decision to use or accept a new technology or system because they feel that these choices affect how they actually use it. According to Davis et al. (1989), behavioural intention (BI) is a measure of a person's intention to engage in a specific action. Blut and Wang (2020) observed that usage habits are comparable to BI. Some of the intentions that prior research has utilised BI to explain are the intention to use (Hwang et al., 2019), recommendations via word-of-mouth (Wang et al., 2019), intents to purchase (Liang & Lim, 2011), and intentions to repurchase (Chauke & Dhurup, 2017). According to Bauerová and Klepek (2017), consumers are more inclined to make more purchases from the same platform following a satisfying online grocery shopping (OGS) experience. Furthermore, prior studies show that BI significantly influences real usage behaviour, especially when it comes to new technologies and systems (Davis et al., 1989; Gumasing et al., 2022). Given these insights and the lack of empirical evidence examining this relationship in OGS, we aim to test this connection in our study. Therefore, we propose the following hypothesis:

H2: Behavioral intention positively influences usage behaviour.

2.5 Elements of behavioural intention and online grocery shopping

2.5.1 Performance expectancy

Performance expectancy in a consumer context refers to "the extent to which technology will benefit consumers in performing specific tasks" (Venkatesh et al., 2012). People are more willing to use technology and are far more satisfied when it helps them with daily work (Sun et al., 2008). In line with the results of earlier studies, performance expectancy (PE) has been identified as a critical factor in influencing users' behavioural intentions to use shopping applications (Gumasing et al., 2022; Chopdar et al., 2018). The following hypotheses were proposed in light of this:

H3a: Task-technology fit positively impacts performance expectancy.

H4a: Performance expectancy influences behavioural intention.

2.5.2 Effort expectancy

As described by Venkatesh et al. (2012), effort expectancy is "the ease with which consumers can use a technology". According to Chopdar et al. (2018), people are more likely to accept new technology if it is useful and simple to use. According to Sun et al. (2008), technology that prioritises usability and provides teaching resources is more likely to be adopted. However, some studies show that effort expectancy has little effect on users' intention to stick with mobile technologies, such as shopping and banking apps (Yuan et al., 2016; Chopdar et al., 2018). After the initial use of mobile devices, users' intentions may no longer be strongly influenced by effort expectancy. These results led to the following theories being put forth:

H3b: Task-technology fit positively impacts effort expectancy.

H4b: Effort expectancy influences behavioural intention.

2.5.3 Social influence

"The degree to which an individual believes that important people think they should use the new system" is known as social influence (Venkatesh et al., 2003). In a similar vein, Rashotte (2007) defines SI as "the ways in which others influence a person's actions, attitudes, emotions, and thoughts, either directly or indirectly." According to UTAUT, SI positively impacts behavioural intention (BI). Studies have shown that SI significantly influences users' decisions to adopt online-to-offline delivery services (Sun et al., 2008). People are more inclined to adopt technology when they believe it will improve their social image (Gumasing et al., 2022). This is consistent with earlier findings (Chopdar et al., 2018) that suggest family, friends, and colleagues can influence someone's intention to use a technology. Based on these insights, the following hypotheses were proposed:

H3c: Task-technology fit positively impacts social influence.

H4c: Social influence influences behavioural intention.

2.5.4 Facilitating conditions

Venkatesh et al. (2012) describes facilitating conditions as "the degree to which a person believes that there is adequate organizational and technical support to enable system use." In online shopping, facilitating conditions refers to having the necessary resources to engage in the shopping process. Taylor and Todd (1995) suggest that lacking FC can hinder engaging in online transactions. Yang (2010) argues that FC directly impacts behavioural intention (BI). Pavlou and Chai (2002) further note that key FC components—such as computer access, reliable Internet connectivity, and customer support—significantly influence Malaysian consumers' decisions to shop online. However, according to the UTAUT model (Venkatesh et al., 2003), FC does not directly affect BI. In light of this, the following hypotheses were put forth:

H3d: Task-technology fit positively affects facilitating conditions.

H4d: Facilitating conditions influence behavioural intention.

2.5.5 Hedonic motivation

Venkatesh et al. (2012) define hedonic motivation as "the fun or pleasure derived from using technology," drawing parallels between it and concepts such as playfulness or enjoyment. Moreover, hedonic motivation is a major factor in determining how users of information technology behave, according to Childers et al. (2001). Adults driven by enjoyment from the internet can influence consumers' intents to browse and buy, according to research done in Taiwan by Liao et al. (2007). Similarly, Topaloğlu's (2012) study, carried out in Turkey, showed that hedonic motivation (HM) positively influences consumers' propensities to shop online. Moreover, Gumasing et al. (2022) found that HM may be improved to produce an enjoyable experience that encourages users to embrace and use new technologies. In light of these findings, the following hypotheses were proposed:

H3e: Task-technology fit positively impacts hedonic motivation.

H4e: Hedonic motivation influences behavioural intention.

2.5.6 Trust

For consumers to intend to shop online, trust is essential (Pavlou & Chai, 2002). Since there are no in-person exchanges between customers and sellers when shopping online, trust becomes essential (Mohseni & Sreenivasan, 2014). Trust is a crucial factor that positively impacts Malaysians' intents to shop online, according to a study by Liat and Wuan (2014). Similarly, Indian consumers' online shopping habit is positively impacted by trust (Gupta & Kumar, 2023). Based on this, the following hypotheses can be proposed:

H3f: Task-technology fit positively affects Trust.

H4f: Trust influences behavioral intention.

2.5.7 Risk

Consumers' perceptions of risk significantly hinder online transactions (Pavlou & Chai, 2002). Risk is also a significant factor affecting the intention to repurchase (Gupta & Kumar, 2023). Perceived risk is commonly recognized as a critical obstacle to any online transaction, and as the perceived level of risk increases, consumers are less likely to proceed with online purchases (Kim et al., 2008). A study conducted in Malaysia found a robust negative relationship between perceived risk and the intention to make an online purchase (Zendehdel & Paim, 2015). Similarly, Gupta and Kumar (2023) confirmed that perceived risk negatively influences consumers' behavioural intentions regarding online grocery shopping (OGS). Based on these findings, the following hypotheses can be proposed:

H3g: Task-technology fit positively affects risk.

H4g: Risk influences behavioral intention.

2.5.8 Cost

Venkatesh et al. (2012) define cost, or price value, as "the consumer's mental evaluation of the balance between the perceived benefits of using an application and the monetary cost involved." Consumers tend to avoid online purchases if prices are too high (Prasad & Raghu, 2018), as they generally seek lower prices from online stores (Khan et al., 2015). They like to compare prices and find the best deal (Venkatesh et al., 2012), and securing such a deal positively affects their behavioural intentions. Based on this, the following hypotheses can be proposed:

H3h: Task-technology fit positively affects cost.

H4h: Cost influences behavioral intention.

2.5.9 Habit

Venkatesh et al. (2012) defines a habit as "the degree to which individuals tend to perform behaviours automatically due to prior learning." Consumers often use services based on their previous experiences, and repeated use of these services can become a habit, influencing their future intentions, including in online shopping (Sun et al., 2008). Similarly, people increasingly rely on their smartphones out of habit when using mobile apps, continuing to do so for online shopping (Amoroso & Lim, 2017). Based on this, the following hypotheses can be proposed:

H3i: Task-technology fit positively affects habit.

H4i: Habit influences behavioral intention.

2.5.10 Promotion

Promotional activities play a crucial part in encouraging the acceptance of technology. It is a key factor influencing consumer behaviour when deciding to use a product or service. Providing promotions is crucial for online grocery retailers to attract customers to shop online (Vrechopoulos & Siomkos, 2001). Prasad and Raghu (2018) also confirmed that promotions positively affect online grocery shopping behaviour, as consumers tend to favor price promotions to manage their finances, with price being a critical factor in online purchasing decisions. Based on this, the following hypotheses are proposed:

H3j: Task-technology fit positively impacts Promotion.

H4j: Promotion influences behavioral intention.

2.5.11 Personal Innovativeness

This is an important aspect to consider when exploring adopting new systems from consumer and organizational perspectives. Hwang et al. (2019) found that individuals with higher PI levels are likelier to adopt online food delivery services. People's attitudes and beliefs about technology are crucial in predicting their behavioural intention (BI) (Davis et al., 1989). Within the UTAUT framework, PI is considered a potential factor influencing BI (Van Droogenbroeck & Van Hove, 2017). During the pandemic, social distancing enhanced the use of internet-based shopping services, and personal Innovativeness in technology further strengthened Trust in these services (Wang et al., 2021). Therefore, the subsequent hypotheses are projected:

H3k: Task-technology fit positively impacts personal Innovativeness.

H4k: Personal Innovativeness influences behavioural intention.

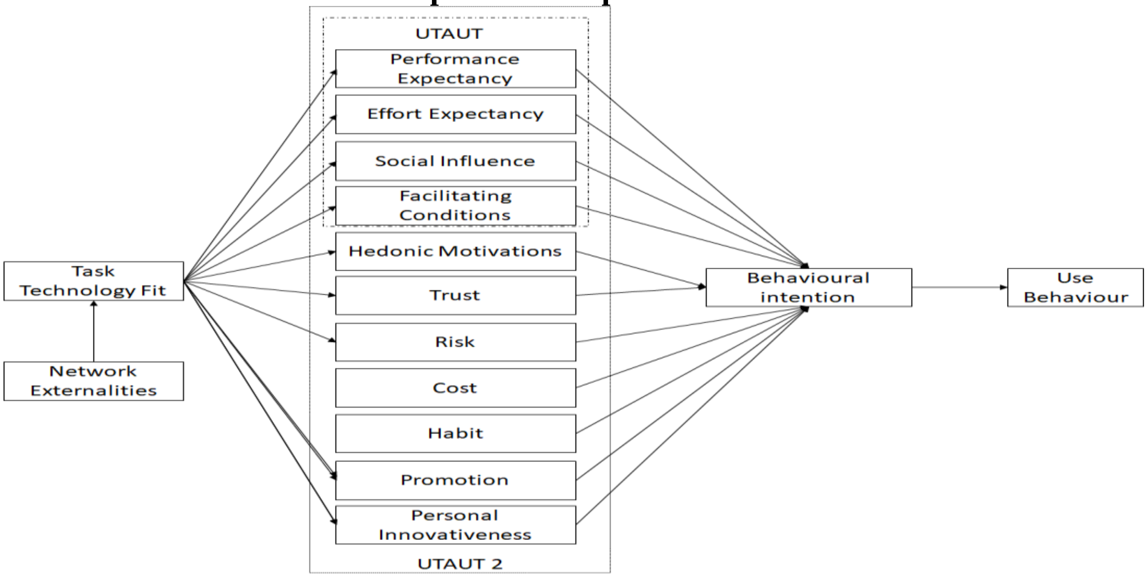
3. RESEARCH METHODOLOGY

3.1 Measurement Instrument

The measurement items for critical constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, cost, habit, and usage behaviour were adapted from the work of Venkatesh et al. (2012). The items for personal Innovativeness were sourced from Hwang et al. (2019), while task-technology fit items were taken from Larsen et al. (2009). The scale for measuring network externalities was based on Kim et al. (2017), and the promotion items were adapted from Yoo et al. (2000). Trust was measured using items from Wang et al. (2015), and risk was assessed using the items developed by Martins et al. (2014). All these measurement scales have been validated in prior studies focusing on consumer behavioural intentions in online shopping contexts. The responses were gathered using a five-point Likert scale, with 1 indicating "Strongly Disagree" and five representing "Strongly Agree." The questionnaire also included six demographic questions covering age, gender, education, income, occupation, and family size.

The closed-ended questionnaire, containing the scales above and demographic questions, was used to collect data from individuals with experience in online grocery shopping. It was distributed online and in-person across India using a cross-sectional convenience sampling method. Participation was voluntary, and no incentives were provided. Data were gathered from four major metropolitan cities in India—Ahmedabad, Mumbai, Delhi, and Pune—between January 2022 and May 2022. Out of 900 respondents approached, 665 valid responses were used for analysis after incomplete submissions were removed.

Figure 1.
Proposed Conceptual Model



4. DATA ANALYSIS

We utilized SmartPLS 3.0, which applies the partial least square method, to test the hypotheses. Initially, we evaluated the constructs' reliability and validity. For reliability, we evaluated internal consistency using Cronbach's alpha and composite reliability. Both Cronbach's alpha and composite reliability scores must exceed 0.70 to show good reliability (Hair Jr et al., 2016).

Next, we measured outer loadings and average variance extracted (AVE) for convergent validity. Outer loadings should be above 0.7 (Bagozzi et al., 1991), and AVE values should exceed 0.5 (Hair Jr et al., 2016). As a result, we removed certain items due to lower loadings. However, per Fornell and Larcker (1981), if composite reliability is above the threshold, an AVE of 0.4 is acceptable. All variables demonstrated moral convergent validity based on these criteria (Table I). Following Hair Jr et al. (2016), discriminant validity was evaluated using the Heterotrait-Monotrait Ratio (HTMT) (Table II).

Table: I
Cronbach's Alpha, Composite Reliability, Average Variance Extracted

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Behavioural Intention	0.842	0.888	0.613
Cost	0.66	0.807	0.584
Effort Expectancy	0.852	0.888	0.532
Facilitating Conditions	0.742	0.818	0.393
Hedonic Motivations	0.808	0.874	0.637
Habit	0.784	0.85	0.493
Network Externalities	0.805	0.862	0.513
Performance Expectancy	0.833	0.878	0.55
Personal Innovativeness	0.667	0.798	0.585
Promotion	0.876	0.91	0.669
Risk	0.898	0.919	0.591
Social Influence	0.843	0.889	0.615
Task-Technology Fit	0.899	0.917	0.503
Trust	0.883	0.912	0.635
Use Behaviour	0.886	0.922	0.746

Note: Own Calculations

Table: II
Discriminant Validity

	BI	CO	EE	FC	HM	HT	NE	PE	PI	PRO	RK	SI	TTF	TT	UB
BI															
CO	0.413														
EE	0.52	0.328													
FC	0.408	0.352	0.721												
HM	0.513	0.415	0.652	0.599											
HT	0.717	0.37	0.447	0.339	0.6										
NE	0.549	0.385	0.514	0.586	0.456	0.558									
PE	0.494	0.316	0.824	0.618	0.617	0.462	0.505								
PI	0.445	0.326	0.263	0.24	0.258	0.383	0.344	0.3							
PRO	0.375	0.267	0.462	0.472	0.516	0.31	0.425	0.364	0.155						
RK	0.28	0.15	0.381	0.336	0.26	0.241	0.246	0.335	0.209	0.124					
SI	0.249	0.225	0.417	0.481	0.445	0.329	0.421	0.387	0.194	0.336	0.162				
TTF	0.599	0.459	0.745	0.687	0.602	0.473	0.601	0.601	0.283	0.511	0.398	0.404			
TT	0.525	0.375	0.663	0.579	0.654	0.53	0.54	0.527	0.236	0.414	0.386	0.359	0.711		
UB	0.787	0.346	0.501	0.403	0.553	0.655	0.477	0.54	0.444	0.296	0.328	0.341	0.542	0.51	

(BI - behavioural intention; CO – Cost; EE - Effort Expectancy; FC - Facilitating Conditions; HM - Hedonic Motivation; HT – Habit; NE - Network Externalities; PE - Performance Expectancy; PI - Personal Innovativeness; PRO – Promotion; Risk – RK; SI - Social Influence; TTF - Task-Technology Fit; TT – Trust; UB - Use Behaviour)

The Variance Inflation Factor (VIF) is used to assess collinearity. According to Hair Jr et al. (2017), collinearity among variables should be evaluated using outer VIF for indicators and inner VIF for latent variables, with VIF values needing to be less than five. In this study, all constructs showed VIF values below five, indicating no multicollinearity issues.

Path coefficients were calculated using bootstrapping, t-statistics, and p-values to test the proposed hypotheses and evaluate the relationships between the variables. Hypothesis H1 explored the relationship between NE and TTF, and the results showed that NE significantly influenced TTF ($T = 13.38$; $\beta = 0.502$; $p = 0.00$).

All hypotheses in H3 were designed to assess the effect of TTF on UTAUT and UTAUT2 constructs. The findings revealed that TTF positively affected all constructs, including PE ($T = 13.10$; $\beta = 0.488$; $p = 0.00$), EE ($T = 16.43$; $\beta = 0.619$; $p = 0.00$), SI ($T = 8.28$; $\beta = 0.387$; $p = 0.00$), FC ($T = 14.88$; $\beta = 0.551$; $p = 0.00$), HM ($T = 14.05$; $\beta = 0.514$; $p = 0.00$), TT ($T = 19.61$; $\beta = 0.613$; $p = 0.00$), CO ($T = 7.89$; $\beta = 0.323$; $p = 0.00$), HT ($T = 8.36$; $\beta = 0.377$; $p = 0.00$), PRO ($T = 11.59$; $\beta = 0.437$; $p = 0.00$), and PI ($T = 5.78$; $\beta = 0.234$; $p = 0.00$). The only exception was RK, which showed a negative impact ($T = 8.73$; $\beta = -0.357$; $p = 0.00$).

All hypotheses in H4 aimed to evaluate the effect of UTAUT and UTAUT2 constructs on behavioural intention. The outcomes indicated that 6 out of 11 constructs significantly impact behavioural intention: EE ($T = 2.543$; $\beta = 0.173$; $p = 0.00$), TT ($T = 1.78$; $\beta = 0.112$; $p = 0.00$), CO ($T = 2.034$; $\beta = 0.131$; $p = 0.00$), HT ($T = 9.023$; $\beta = 0.369$; $p = 0.00$), PRO ($T = 2.154$; $\beta = 0.084$; $p = 0.00$), and PI ($T = 3.769$; $\beta = 0.149$; $p = 0.00$).

Finally, Hypothesis H2 examined the influence of behavioural intention on actual use behaviour, and the results confirmed a positive relationship ($t = 23.134$; $\beta = 0.756$; $p = 0.00$). The full results of the hypothesis testing are summarized in Table III.

Table: III
Bootstrapping Outcomes and Path coefficients

Sr. No.	Paths	T Statistics	β values	p values	Hypothesis support
H1	NE→TTF	13.38	0.502	0	**Yes**
H3a	TTF→PE	13.10	0.488	0	**Yes**
H3b	TTF→EE	16.43	0.619	0	**Yes**
H3c	TTF→SI	8.28	0.387	0	**Yes**
H3d	TTF→FC	14.88	0.551	0	**Yes**
H3e	TTF→HM	14.05	0.514	0	**Yes**
H3f	TTF→TT	19.61	0.613	0	**Yes**
H3g	TTF→RK	8.73	-0.357	0	**Yes**
H3h	TTF→CO	7.89	0.323	0	**Yes**
H3i	TTF→HT	8.36	0.377	0	**Yes**
H3j	TTF→PRO	11.59	0.437	0	**Yes**
H3k	TTF→PI	5.78	0.234	0	**Yes**
H4a	PE→BI	1.139	0.061	0.248	**No**
H4b	EE→BI	2.543	0.173	0	**Yes**
H4c	SI→BI	1.329	-0.048	0.142	**No**
H4d	FC→BI	0.032	0.001	0.823	**No**
H4e	HM→BI	0.228	0.007	0.763	**No**
H4f	TT→BI	1.78	0.112	0	**Yes**
H4g	RK→BI	1.128	-0.032	0.193	**No**
H4h	CO→BI	2.034	0.131	0	**Yes**
H4i	HT→BI	9.023	0.369	0	**Yes**
H4j	PRO→BI	2.154	0.084	0	**Yes**
H4k	PI→BI	3.769	0.149	0	**Yes**
H2	BI→UB	23.134	0.756	0	**Yes**

Note: Own Calculations

5. DISCUSSION AND CONCLUSION

Increased online grocery shopping usage has captured the interest of both researchers and marketers. With the increasing number of online shoppers, marketers must understand what motivates consumers to order groceries online to gain a competitive edge. The primary objective of this research is to recognize the features that drive users to accept online food delivery services. A secondary goal is to analyze the key elements that impact users' intentions to adopt and use online food delivery. Additionally, the study aims to provide a unified conceptual model. The UTAUT and UTAUT2 models were integrated with TTF and NE within the UTAUT framework to achieve these objectives. Another aspect of this study is to examine the direct consequence of NE on TTF and the indirect impact of TTF on UTAUT2 constructs.

The initial hypothesis examined the connection between NE and TTF, revealing a positive and significant association. This suggests that as the consumer base for online grocery shopping grows, people believe that the technology helps them efficiently complete their tasks. TTF has a significant positive connection with PE, indicating that when appropriate technology is available, users experience improved performance. Similarly, a positive link was observed between TTF and EE, suggesting that users find it easier to place online grocery orders with minimal effort, supported by Baxi and Patel (2021).

Furthermore, TTF demonstrated a significant positive relationship with social influence, indicating that peer associates and household members influence online grocery service users. The findings align with those of Zhao and Bacao (2020), although there are differences Baptista and Oliveira (2015) revealed on the use of mobile wallets among younger users in particular. An increasing number of people are shopping for groceries online, which has created a need for favourable conditions, or supporting infrastructure. According to Baptista and Oliveira (2015), TTF in this study was positively correlated with facilitating factors, indicating that users have access to the infrastructure, technology, and tools needed to buy for food online.

Additionally, TTF showed a positive correlation with both risk and trust, indicating that, as

Baxi and Patel (2021) support, customers feel safe placing online grocery orders because they have faith in the system to safeguard their personal information, financial transactions, and product deliveries. Additionally, a positive correlation between TTF and cost was discovered, suggesting that customers believe online grocery buying to be more economical than traditional purchasing—a perspective that is corroborated by Prasad and Raghu (2018). TTF also had a favourable impact on consumer behaviour, indicating that it facilitates the development of an online grocery ordering pattern.

TTF had a favourable impact on promotions, both monetary and non-monetary, confirming that users are motivated by incentives. Additionally, there was a significant correlation found between TTF and Personal Innovativeness, indicating that those who are receptive to new ideas are more likely to use online grocery shopping.

Performance expectancy was shown to have no significant impact on behavioural intention when the direct links between UTAUT and UTAUT2 components and behavioural intention were examined. This implies that consumers don't think doing their grocery shopping online makes them more productive. Gumasing et al.'s research from 2022, on the other hand, showed a significant relationship between behavioural intention and performance expectancy. The results of Chopdar et al. (2018) likewise showed that social influence had no appreciable impact on consumers' inclinations to switch to online grocery shopping. Furthermore, the facilitation conditions had no discernible impact on behavioural intention, suggesting that physical infrastructure had no bearing on customers' intentions to shop online. This is contrary to the findings of Venkatesh et al. (2003) and Gumasing et al. (2022), even if it is consistent with the conclusions made by Pavlou and Chai (2002), who stressed the significance of resources and skills in technology adoption.

It is significant to discover that behavioural intention was unaffected by hedonic reward. This result supports the findings of Gumasing et al. (2022) and implies that consumers' opinions towards technology use are not influenced by how satisfied they are with online grocery shopping. Furthermore, contrary to Zendehdel and Paim's (2015) findings, which indicated a negative association between risk and behavioural intention in online grocery shopping, users' intention to shop did not change as a result of the risk.

However, significant positive relationships were identified between effort expectancy, Trust, cost, habit, Promotion, and personal Innovativeness with users' intentions to shop for groceries online. Effort expectancy positively affects behavioural intention, although Gumasing et al. (2022) found no such effect. Trust, cost, and habit also played significant roles in shaping consumer intentions, with users preferring to purchase groceries at lower costs, and once accustomed to online grocery shopping, it became a habitual action (supported by Agarwal and Sahu, 2021). Promotions had a significant positive effect, encouraging users to shop online, consistent with findings from Prasad and Raghu (2018). Lastly, personal Innovativeness has a positive relationship with behavioural intention, with consumers drawn to innovative ways of ordering groceries online (Van Droogenbroeck & Van Hove, 2021).

In summary, this study identified several factors that influence the use of online grocery shopping services. These findings align with previous research, with the Slovenian study suggesting that performance expectancy remains a crucial factor while social influence has a minimal effect. The COVID-19 pandemic has further accelerated the adoption of online grocery shopping in India, supporting earlier research that calls for integrating the UTAUT2 model with other theories to explore new contextual effects (Venkatesh et al., 2012).

6. IMPLICATIONS

Online grocery shopping is becoming one of the most convenient ways for consumers to purchase groceries, allowing them to order from anywhere at any time. Moreover, consumers can choose their preferred grocery items from various vendors, increasing flexibility. The growing use of online platforms for grocery shopping has drawn the attention of managers seeking to gain a competitive edge. Grocery online retailers must create effective strategies to attract more customers by identifying and leveraging the factors that encourage people to shop for groceries through their platforms. To encourage repeat platform use, these retailers should provide proper support and assistance when issues arise, such as delivering the wrong parcel.

From a business perspective, the application development teams of organizations should focus on improving existing apps or websites to deliver better performance for consumers, grocery business owners, and service providers. As online grocery shopping becomes more popular, competition will intensify, increasing the need for seamless user experiences and the effective use of data generated from these platforms. Creating an ecosystem that enhances user performance and satisfaction will allow existing players to strengthen their services. For consumers, this would mean access to more real-time information, reducing uncertainties related to service quality. Additionally, users could benefit from more promotional offers and improved service quality as vendors strive to outperform competitors.

One key role of this study is to provide a unified theoretical framework within the information systems domain. To meet the study's objectives, two well-established theories—UTAUT and UTAUT2—were combined to comprehensively understand the factors influencing consumers' intentions to order groceries online. Unlike previous studies that generally focused on direct or indirect relationships within a single theory, this research uniquely examines the indirect influence of one theory on another.

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