# From Necessity to Pleasure: The Impact of Hedonic Motivation and Performance Expectancy on Acceptance of Online Grocery Shopping Apps in Germany

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# **ABSTRACT**

This study investigates key factors influencing German consumers' acceptance of online grocery shopping (OGS) apps. Despite the growing popularity of e-commerce, research on OGS app adoption in Germany remains limited. We applied the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model to examine factors affecting acceptance and behavioral intention to use OGS apps. A quantitative approach with a convenience sample was employed in Germany. Data analysis involved principal component analysis followed by multiple linear regression analyses using IBM SPSS 28. Results showed that performance expectancy, hedonic motivation, and previous use of OGS apps significantly influenced behavioral intention. The UTAUT2 model's predictive probability was highest when considering control variables such as gender, age, and previous app use. Our findings contribute to understanding OGS app adoption in Germany and suggest practical implications, including expanding delivery zones to rural areas. This research addresses the knowledge gap in OGS app acceptance in Germany and provides insights for researchers and practitioners in the food retail sector.

### **KEYWORDS**

Online grocery shopping apps, German retail, UTAUT2 model, behavioral intention

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# 1. Introduction

The advent of online grocery shopping (OGS) apps has revolutionized the way consumers purchase their daily necessities, offering unprecedented convenience and accessibility (Shroff et al., 2024). In recent years, OGS has experienced significant growth worldwide (Dillahunt et al., 2019). It allows users to order groceries conveniently on the internet and have them delivered to their desired location by the provider (Al-nawayseh et al., 2013; Musikavanhu & Musakuro, 2023). In 2022, the internet sales of food, including beverages and tobacco, accounted for 2.4 % of retail sales in Germany. This share has been steadily increasing since 2014 (Handelsverband Deutschland (HDE) e.V., 2024). Additionally, online grocery sales increased significantly in Germany from 2014 to 2022. By 2023, around EUR 11.3 billion had already been generated from groceries purchased online (Bundesverband E-Commerce und Versandhandel Deutschland (BEVH) e.V., 2024). Due to the rising demand for OGS apps, more and more providers—for example, Flink and Gorillas—have entered the German market. Users can choose the app that best suits their needs (Handelsverband Deutschland (HDE) e.V., 2024). Yet many customers have not yet adopted OGS apps despite their increasing popularity (Brüggemann et al., 2024).

The shift in consumer behavior toward online shopping requires traditional brick-and-mortar stores to adapt by enhancing their online presence and integrating digital solutions into their business strategies (Shroff et al., 2024). Retailers might need to invest in new technologies and logistics to support online orders and deliveries, including efficient supply chain management systems, warehouse automation, and last-mile delivery solutions (Frank & Peschel, 2020).

Although extensive research has been conducted on the factors affecting acceptance of OGS apps during and after the COVID-19 pandemic (Asgari et al., 2023; Gruntkowski & Martinez, 2022; Shen et al., 2022; Younes et al., 2022), as well as their adoption in various countries, including South Africa (Musikavanhu & Musakuro, 2023), India (Gupta & Kumar, 2023), the Netherlands (Verhoef & Langerak, 2001), the United States (Gillespie et al., 2022) and Thailand (Driediger & Bhatiasevi, 2019), there is a need to better understand consumers' usage intentions relative to these apps in Germany. Studies in the German context have focused predominantly on the pandemic period, examining the perspectives of retailers or elderly consumers (Braun & Osman, 2024; Hansson et al., 2022; Kvalsvik, 2022). However, the primary users of OGS apps are typically younger individuals between 20 and 29 years old residing in urban areas (Handelsverband Deutschland (HDE) e.V, 2024).

The purpose of this research was to fill a research gap identified by Monoarfa et al. (2024) and Klepek and Bauerová (2020) by investigating the factors that influence consumers' acceptance of OGS apps and their hesitancy about continuing to use them. The study aimed to explore the implications of broadly implementing OGS apps and provide insights to app developers and retailers who want to implement them. Therefore, seven hypotheses were tested based on an extension of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. The UTAUT2 model is an extended version of the original UTAUT model that was developed to better explain technology acceptance, particularly in consumer contexts (Venkatesh et al., 2012). It extends the original framework by incorporating additional factors such as hedonic motivation, such as the pursuit of pleasure and enjoyment, price value, and habits, which significantly influence consumer acceptance and use of new technologies (Indrawati et al., 2022). Hedonic motivations can lead to increased consumer impulsiveness and more extended engagement with shopping platforms, thereby enhancing the overall shopping experience (Yim et al., 2014). This study examined the role of hedonic motivations in the context of OGS apps to understand how pleasure-driven factors impact user intentions. The primary objectives of this research were to

- apply technology adoption theories to understand the acceptance and usage patterns of OGS apps.
- identify the key factors influencing the intention to use OGS apps in Germany.

In addition, the model considered control variables such as age, gender, and previous use (Singh & Söderlund, 2020) to ensure a comprehensive analysis. Although this study employed a convenience

sample, unlike previous studies, a video based on a market analysis that explains all essential functionalities of OGS apps, such as automatic location detection and digital shopping lists, was produced. This ensured that the questionnaire could be answered effectively by both users and non-users. Furthermore, this study examined not only internationally known apps such as Flink and Gorillas but also apps unique to Germany, including Flaschenpost and the REWE delivery service app.

By addressing this under-researched area, we aimed to provide a comprehensive understanding of the motivations and barriers associated with OGS app usage, thereby contributing valuable insights into consumer behavior and retailing. The structure of this paper is as follows: The following section presents the theoretical background, including the UTAUT2 model. Subsequently, we detail the methodology and data collection process and discuss the survey participants' demographics. Then, we examine the statistical analysis and present the results. Finally, the managerial implications of the findings are discussed, providing insights for practitioners on how to enhance the adoption and usage of OGS apps.

# 2. Theoretical Background

This study applied the UTAUT2 model by Venkatesh et al. (2012) to examine consumer behavior relative to the acceptance of OGS apps. The application of the UTAUT2 model was based on questions about several factors that were progressively asked of the technology user. These factors included performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, and behavioral intention (Venkatesh et al., 2012). Well-founded predictions could be made about whether OGS apps would be accepted with the information generated from these factors. The following segments describe how the factors were applied in the UTAUT2 model.

### Performance Expectancy

When technology is used to complete a task or achieve a goal, performance expectancy (PE) describes the degree to which a person believes the outcome will be achieved (Park et al., 2007; Venkatesh et al., 2003). The PE construct is considered the strongest and most significant predictor of intention (Alalwan et al., 2017; Hassan et al., 2015; Musakwa & Petersen, 2023; Venkatesh et al., 2003). In this study, PE reflected the app user's expectation of an online grocery shopping experience. Factors that lead to an improved overall experience when using an app include, for example, an easy ordering process, an extensive product selection, and the timely and reliable delivery of groceries (Venkatesh, 2006). Accordingly, we hypothesized that having an ordering process that meets high-performance expectations could influence the acceptance of OGS apps.

**H01** Expected performance positively influences the behavioral intention to use OGS apps.

# Effort Expectancy

Whether the use of the technology is perceived as easy is reflected in effort expectancy (EE) (Venkatesh, 2006). OGS apps are evaluated for user-friendliness by the consumer, whose perception of ease of use plays an important role (Park et al., 2007). The usability of grocery shopping apps is characterized by factors that meet a reasonable expectation of effort, such as user-friendly interfaces, self-explanatory ordering processes, search functions, and different payment options. Therefore, we formulated the following hypothesis for this component:

**H02** *EE positively influences the behavioral intention to use OGS apps.* 

### Social Influence

The extent to which factors such as social media, social norms, or product recommendations from friends and family influence the use of OGS apps was examined in this study through the consideration of social

influence (SI). The SI of a particular technology defines individuals' perception of the importance that others place on its use (Venkatesh et al., 2003; Zolfaghari et al., 2022). The UTAUT2 model was used to examine whether and to what extent social factors influence the user's decision to order food through the app. For instance, personal recommendations may influence a decision whether to use an OGS app or shop at a regular supermarket.

**H03** SI positively affects the behavioral intention to accept OGS apps.

## Facilitating Conditions

Another component of the UTAUT2 model is facilitating conditions (FC) (Venkatesh, 2006). The FC are primarily intended to catch and support users who are uncertain about using the apps as that uncertainty may cause them to discontinue their use (Morris et al., 2005). To make OGS apps accessible and understandable to all age groups, support systems such as customer support and training on how to use the apps are essential.

**H04** FC positively influences the behavioral intention to accept OGS apps.

### Hedonic Motivation

The satisfaction and enjoyment derived from using OGS applications can serve as a source of hedonic motivation (HM) for continued usage (Brown & Venkatesh, 2005). Emotional factors are deemed significant in the development of OGS applications (Thong et al., 2006). Attributes such as age, origin, and gender influence hedonic motivation, as individuals find different aspects pleasurable based on their circumstances (Yim et al., 2014). Experiences such as discovering new products, enjoying a streamlined shopping process, or receiving personalized recommendations can contribute to the desired satisfaction from the application (Taglinger et al., 2023).

**H05** HM positively influences the behavioral intention to accept OGS apps.

# Price Value

Price value (PV) is the customer's perception of the value received in exchange for money (Brown & Venkatesh, 2005). This prompts consideration of the extent to which the benefits of an OGS app outweigh its cost. For a technology to be successful in the long run, its benefits must be superior to the financial costs (Zeithaml, 1988). For instance, high delivery costs may discourage a user from utilizing OGS apps. Additionally, age and gender play a role in people's attitudes toward value for money (Deaux & Lewis, 1984).

**H06** The expected PV positively influences the behavioral intention to accept OGS apps.

# Habit

The process by which behavior becomes automated, transitioning from the initial stages of learning to frequent utilization of technology, is defined as habit (HA) (Limayem et al., 2007; Venkatesh et al., 2012). OGS apps should be adopted more frequently due to their substantial benefits, including time efficiency and convenience for customers, according to Verhoef and Langerak (2001). Additionally, the habitual use of these apps can enhance the intention to use them, as it facilitates the acceptance and integration of this innovative service into consumers' everyday routines. This study investigated the habitual use of Online Grocery Shopping (OGS) applications to ascertain the frequency and regularity with which groceries were ordered through these platforms. The development of habitual use of OGS applications was examined under the following hypothesis.

**H07** *HA* positively influences the behavioral intention to accept OGS apps.

### Behavioral Intention

Behavioral intention (BI) is a person's intention to do something—in this case, to use an OGS app. Factors that influence BI include how skillfully a customer uses the app, whether the benefits of the app are perceived as such, and whether the app has satisfied users in the social environment (Liu et al., 2019). The usage behavior of OGS app consumers is influenced by their expectations of performance and effort, the social environment, facilitating technological circumstances, hedonic motivation, the perceived price-performance ratio, and the habit of purchasing groceries via an app. This section of the UTAUT2 encompasses the factors previously discussed, making BI a dependent variable and the principal component of this analysis (Musikavanhu & Musakuro, 2023), as seen in Figure 1.

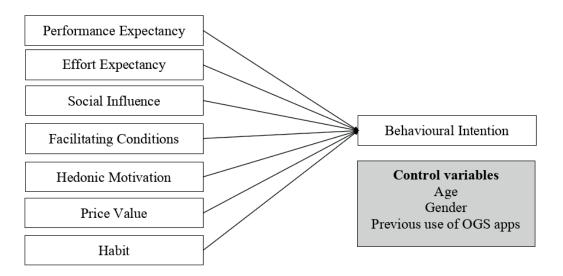


Figure 1: UTAUT2 Model and Control Variables. Source: Venkatesh et al. (2012)

This study considered several control variables to ensure a robust analysis of the factors influencing the intention to use OGS apps. These control variables included age, gender, and previous use of OGS apps (Frank & Peschel, 2020). Age is critical as it can influence technology adoption, with younger individuals often being more open to new technologies (Braun & Osman, 2024). Gender was also considered, as research has shown that men and women may have different attitudes toward technology use and other related behaviors (Qazi et al., 2022). Previous use of OGS apps was included to account for familiarity and experience with the technology, which can significantly impact the intention to continue using the technology. We incorporated these control variables to provide a nuanced understanding of the determinants of OGS app usage intentions.

# 3. Methodology

Our study was conducted across Germany using an online questionnaire. For the analysis, we collected postal codes (*Postleitzahlen*, *PLZ*) and additional information on the population size of the participants' residential areas. This allowed us to categorize the regions as either rural or urban, providing a nuanced understanding of the data.

As we distributed the survey via the Internet, German citizens from various regions could participate, ensuring an accurate representation of current attitudes toward OGS apps in Germany. Additionally, no personally identifiable information was gathered that could influence the outcomes. The target audience consisted of German residents, regardless of their familiarity with OGS. The entire methodology and

approach are illustrated in the flowchart in Figure 2.

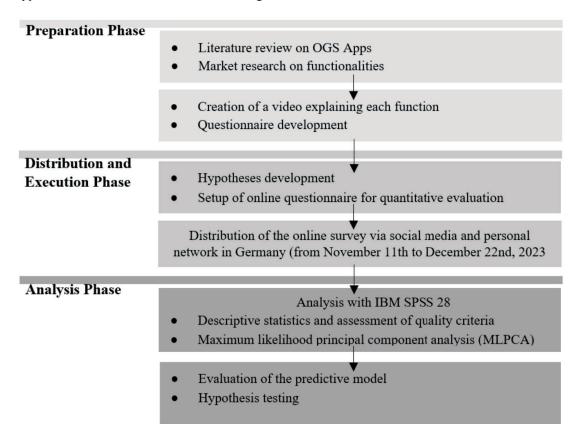


Figure 2: Flow Chart of Methodology. Source: Created by the authors.

The survey structure was inspired by work from Netscher et al. (2024) with an explanatory video created by the research team, which introduced the OGS apps to the participants (cf. Appendix). This video illustrated the entire customer journey, starting with registration and address entry, followed by the grocery shopping experience, and concluding with the processing and payment of the order. Each action was depicted with in-app scenes, accompanied by subtitles written by the researchers and audio dubbing to describe the processes shown. The essential functions of OGS apps were demonstrated using anonymized brands to maintain neutrality.

Following the introduction, participants were asked general questions about their experience with OGS apps and their preferred functionalities for optimal usage. The main section of the survey measured the UTAUT2 constructs, with each item evaluated using a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree) (cf. Table 1). As the survey was conducted in Germany, the statements were translated into German, starting from the UTAUT2 model validated questions published by Harborth and Pape (2018) and refined based on the recommendations of a native speaker, following the approach of Taglinger et al. (2023). The survey was pretested for comprehensibility with members of the target audience.

In the final part of the questionnaire, information on the control variables was collected, including the respondents' demographic details (e.g., gender, age, educational status, and income level) and whether they had used OGS apps previously.

| Model Constructs                | Items  |  |  |
|---------------------------------|--|--|--|
| PE (Performance<br>Expectancy)  | PE1: I find food delivery apps useful in my daily life. PE2: Using such an app increases my chances of achieving things that are important to me. PE3: Using such apps helps me complete my shopping faster. PE4: Using food delivery apps increases my productivity.  |  |  |
| EE (Effort Expectancy)          | EE1: It is easy for me to handle these apps. EE2: My use of the apps is clear and understandable. EE3: I find using food delivery apps easy. EE4: It is easy for me to become skilled at using the apps.   |  |  |
| SI (Social Influence)           | SI1: People who are important to me think that I should use such apps. SI2: People who influence my behavior think that I should use such apps. SI3: People whose opinions I value prefer that I use food delivery apps.   |  |  |
| FC (Facilitating<br>Conditions) | FC1: I have the necessary resources to use such apps. FC2: I have the necessary knowledge to use these apps. FC3: These apps are compatible with other technologies and applications I use. FC4: I can get help from others when I have difficulties using these apps. |  |  |
| HM (Hedonic Motivation)         | HM1: Using food delivery apps is fun. HM2: Using food delivery apps is enjoyable. HM3: Using the apps is very entertaining.  |  |  |
| HA (Habit)                      | HA1: Using such apps has become a habit for me. HA2: I am addicted to using food delivery apps. HA3: I must use food delivery apps. HA4: Using these apps has become something natural for me.   |  |  |
| PV (Price Value)                | PV1: Food delivery apps are reasonably priced. PV2: The apps offer good value for the money. PV3: At the current price, these apps offer good value.   |  |  |
| BI (Behavioral Intention)       | BI1: I intend to use food delivery apps in the future. BI2: I will try to use food delivery apps in my daily life. BI3: I plan to continue using such apps regularly.  |  |  |

Table 1: Constructs with Scale Items and Sources. Source: Harborth and Pape (2018)

The survey was distributed through various social media platforms like Facebook, Instagram, WhatsApp, and LinkedIn. The data collection took place from November 11th to December 22nd, 2023. After excluding respondents under 18, incomplete questionnaires, and those with repeated responses without

variance, the final convenience sample consisted of 181 participants. Of these, 58.9 % were female and 41.1 % male, with a mean age of 33.66 years (SD = 11.44; range = 19–67 years) and an average net household income of around  $\epsilon$ 3,000 per month. The gender distribution of the OGS app users was balanced, with 47.9 % being male and 52.1 % female. Additionally, 62.8 % of users were under age 35, indicating a correlation between age and the use of OGS apps (Rakhman et al., 2021). Table 2 provides more detailed information on the demographics of the respondents.

| Measure                          | Absolute values     | Percentage values |  |
|----------------------------------|---------------------|-------------------|--|
| Gender                           | Male                | 41.1 %            |  |
| Gender                           | Female              | 58.9 %            |  |
|                                  | < 25 years          | 24.4 %            |  |
|                                  | 25 - 34 years       | 38.4 %            |  |
| Age group                        | 35 - 44 years       | 21.1 %            |  |
|                                  | 45 - 54 years       | 7.2 %             |  |
|                                  | > 54 years          | 8.9 %             |  |
|                                  | 0 − 1000 €          | 14.4 %            |  |
|                                  | 1001 – 2000 €       | 21.1 %            |  |
|                                  | 2001 – 3000 €       | 23.9 %            |  |
| Monthly income (net)             | 3001 – 4000 €       | 17.2 %            |  |
|                                  | 4001 − 5000 €       | 12.8 %            |  |
|                                  | 5000+€              | 10.6 %            |  |
|                                  | Student             | 23.9 %            |  |
|                                  | Jobseeker           | 2.8 %             |  |
|                                  | Employed            | 62.2 %            |  |
| <b>Employment status</b>         | Self-employed       | 6.1 %             |  |
|                                  | Civil servant       | 4.4 %             |  |
|                                  | Retired             | 0.6 %             |  |
|                                  | Urban               | 18.5 %            |  |
| Locale of residence <sup>a</sup> | Rural               | 74.7 %            |  |
| Locale of restuence              | Invalid             | 6.8 %             |  |
|                                  | mvana               | 0.0 /0            |  |
| Provious use of OCS serve        | Not used previously | 60.8%             |  |
| Previous use of OGS apps         | Previously used     | 39.2%             |  |

<sup>&</sup>lt;sup>a</sup> Classification is determined by the location of the residence within or outside the delivery area. Unserviced regions are classified as rural, while those serviced are classified as urban. Invalid cases could not be classified.

Table 2: Sociodemographic Characteristics of Participants. Source: Own research, 2024, n=181.

# 4. Analysis and Results

The utilization of OGS apps was examined in detail, revealing interesting trends among users. While participants reported using well-known OGS apps such as Flink (26 %) and Gorillas (21 %), the most frequently mentioned app was that of the retailer REWE (35 %) (cf. Figure 3). This indicates a preference for established retail brands in the OGS market, suggesting that traditional retailers may have a competitive advantage in attracting and retaining users through their dedicated apps. In contrast, more minor delivery services such as Wolt (6 %) and Getir (9 %) and niche players such as Bringmeister, Picnic, and Knuspr (1 % each) accounted for a smaller share of reported usage, highlighting their more limited market penetration or familiarity among surveyed users.

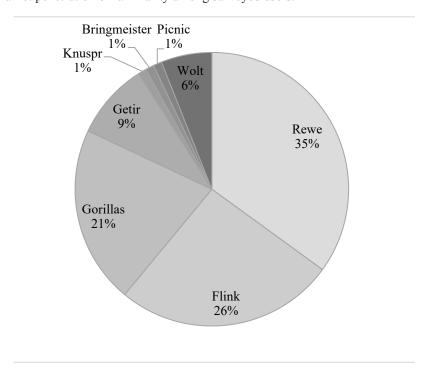


Figure 3: Apps Used by the Respondents.

All survey participants were asked to indicate which devices they preferred for app usage. The majority used smartphones (86 %), but some also used tablets or laptops (9 %), and a notable percentage (5 %) used smartwatches. This highlights the importance of ensuring app compatibility across various devices to meet user preferences and enhance accessibility.

To explore the relationship between these characteristics and the intention to use OGS apps, we performed a statistical analysis of the data using IBM SPSS 28 software. Before testing the proposed research model and its associated hypotheses, the collected constructs were assessed using a maximum likelihood principal component analysis (MLPCA) and evaluated for their statistical quality through reliability tests and descriptive analyses of the scales. An MLPCA is a statistical technique for analyzing a dataset containing intercorrelated dependent variables. The objective is to extract the essential information from the dataset and express it as a reduced number of variables, known as main components. To ascertain the suitability of the data for an MLPCA, the Kaiser-Meyer-Olkin measure (KMO) was employed to assess the adequacy of the sample (Johnson & Wichern, 2007). Bartlett's sphericity test was employed to ascertain the significance of the statements within the dataset. The KMO criterion is calculated from the partial correlations between item pairs. Some authors recommend a minimum value of 0.5 (Backhaus et al., 2015; Cleff, 2015), while others suggest a value of 0.6 (Hartmann & Reinecke, 2013; Tabachnick & Fidell, 2014). The dataset in question exceeded both thresholds, with a value of

0.881. The Bartlett test was employed to investigate the null hypothesis that the correlation matrix was an identity matrix. The p-value was less than 0.001, which was statistically significant, allowing for further analysis (Johnson & Wichern, 2007). Table 3 illustrates the outcomes of the MLPCA, along with the measures of the constructs' reliability (Cronbach's alpha and composite reliability) and validity (average extracted variance). Due to utilizing the UTAUT2 framework, eight components, as described in Section 2, were employed in the factor analysis.

The MLPCA indicated that all UTAUT2 items except HM2 exhibited loadings exceeding 0.6, demonstrating a strong association with the underlying constructs. As Cronbach's alpha values of the HM construct also showed an improvement when item HM2 was excluded, this item was left out from further analysis. The other favorable results can be attributed to the fact that the UTAUT2 is a model that has been subjected to extensive evaluation, and established scales were employed.

| Model<br>Constructs | Indicators | Loadings | Cronbach's<br>Alpha (CA) | Average Variance<br>Extracted (AVE) | Composite Reliability (CR rho_A) |
|---------------------|------------|----------|--------------------------|-------------------------------------|----------------------------------|
| Performance         | PE1        | 0.892    | 0.912                    | 0.790                               | 0.919                            |
| Expectancy          | PE2        | 0.882    |                          |                                     |                                  |
| (PE)                | PE3        | 0.893    |                          |                                     |                                  |
|                     | PE4        | 0.888    |                          |                                     |                                  |
| Effort              | EE1        | 0.942    | 0.948                    | 0.862                               | 0.994                            |
| Expectancy          | EE2        | 0.965    |                          |                                     |                                  |
| (EE)                | EE3        | 0.960    |                          |                                     |                                  |
|                     | EE4        | 0.841    |                          |                                     |                                  |
| Social              | SI1        | 0.947    | 0.949                    | 0.907                               | 0.954                            |
| Influence (SI)      | SI2        | 0.962    |                          |                                     |                                  |
|                     | SI3        | 0.948    |                          |                                     |                                  |
| Facilitating        | FC1        | 0.893    | 0.863                    | 0.785                               | 0.868                            |
| Conditions          | FC2        | 0.879    |                          |                                     |                                  |
| (FC)                | FC3        | 0.884    |                          |                                     |                                  |
|                     | FC4        | 0.679    |                          |                                     |                                  |
| Hedonic             | HM1        | 0.911    | 0.885                    | 0.805                               | 0.973                            |
| Motivation          | HM2        | 0.900    |                          |                                     |                                  |
| (HM)                | HM3        | 0.880    |                          |                                     |                                  |
|                     | HA1        | 0.874    | 0.786                    | 0.706                               | 0.871                            |
| Habit (HA)          | HA2        | 0.543    |                          |                                     |                                  |
|                     | HA3        | 0.682    | no further               | consideration                       |                                  |
|                     | HA4        | 0.928    |                          |                                     |                                  |
| Price Value         | PV1        | 0.881    | 0.912                    | 0.848                               | 0.969                            |
| (PV)                | PV2        | 0.921    |                          |                                     |                                  |
|                     | PV3        | 0.958    |                          |                                     |                                  |
| Behavioral          | BI1        | 0.962    | 0.958                    | 0.922                               | 0.958                            |
| Intention (BI)      | BI2        | 0.966    |                          |                                     |                                  |
| ( )                 | BI3        | 0.953    |                          |                                     |                                  |

Table 3: Descriptive Statistics and Tests for Reliability, N = 181.

As evidenced in Table 3, all constructs exhibited values that aligned with statistical quality, as indicated by Cronbach's alpha values exceeding 0.7, AVE (average variance extracted) surpassing 0.5, and composite reliability falling within the 0.7 to 0.95 range as proposed by Lee (2009), Yu (2010), and Hair et al. (2022). Table 4 illustrates the HTMT (heterotrait-monotrait) ratios proposed by Henseler et al. (2015) for evaluating the discriminant validity of variance-based analyses. All HTMT ratios were found to be below the threshold of 0.85, indicating sufficient discriminant validity and confirming the robustness of the measurement model.

|    | PE       | EE       | SI       | FC       | HM       | PV       | Н        | BI    |
|----|----------|----------|----------|----------|----------|----------|----------|-------|
| PE | 0.782    |          |          |          |          |          |          |       |
| EE | 0.433*** | 0.873    |          |          |          |          |          |       |
| SI | 0.511*** | 0.254*** | 0.877    |          |          |          |          |       |
| FC | 0.290*** | 0.556*** | 0.124*** | 0.754    |          |          |          |       |
| НМ | 0.534*** | 0.334*** | 0.490*** | 0.210*** | 0.797    |          |          |       |
| PV | 0.527*** | 0.414*** | 0.288*** | 0.416*** | 0.434*** | 0.841    |          |       |
| Н  | 0.597*** | 0.246*** | 0.484*** | 0.183*** | 0.418*** | 0.379*** | 0.776    |       |
| BI | 0.782*** | 0.352*** | 0.429*** | 0.265*** | 0.480*** | 0.429*** | 0.613*** | 0.806 |

Table 4: Heterotrait-Monotrait Ratio (HTMT); N = 181.

These constructs were then used in multiple linear regression (MLR) to test the hypotheses derived from the adapted UTAUT2 model.

# 5. Results

Following the formation of the constructs using an MLPCA and the implementation of a series of tests to assess the statistical quality of the collected data, a two-stage, hierarchical MLR was conducted. Other studies have demonstrated that age, gender (Netscher et al., 2024), and previous usage behavior (Frank & Peschel, 2020) influence future BI. Consequently, these criteria were the control variables used in model (0) (Deaux & Lewis, 1984).

In the second step, the study examined the influence of the UTAUT2 components, PE, EE, SI, FC, HM, PV, and HA, on the dependent variable BI. Table 5 illustrates the quality of these models and the coefficient of determination (adjusted R<sup>2</sup>). The statistical significance of the change was calculated to ascertain whether the additional variance (R<sup>2</sup>) could markedly enhance the model. Model (0) indicates that the control variables accounted for 39.3 % of the explained variance of the main component. In contrast, Model (1), which comprises the seven UTAUT2 constructs, exhibits an explanatory variance

of 63.0 %. By combining the control variables with the seven UTAUT2 components, a model was generated that achieved an explanatory variance of 68.8 %. All three models demonstrated statistically highly significant p-values of less than 0.001.

A subsequent multiple regression with a stepwise inclusion of parameters was conducted to ascertain which factors exerted the greatest influence on the modeling of BI. The model exhibited the highest quality with an adjusted R-squared value of 0.694. The key influencing factors were PE, previous use of OGS apps, and HM. This result was corroborated by examining our initial hypotheses (Table 6).

| Model            | Predictors                              | adj, R <sup>2</sup> | $\mathbb{R}^2$ | p         |
|------------------|---|---------------------|----------------|-----------|
| (0) <sup>a</sup> | Control variables                       | 0.393               | 0.403          | <0.001*** |
| (1) <sup>b</sup> | UTAUT 2 construct                       | 0.630               | 0.644          | <0.001*** |
| (2)°             | Control variables and UTAUT 2 construct | 0.688               | 0.705          | <0.001*** |

<sup>&</sup>lt;sup>a</sup> Model (0): Predictors = Gender, Age, Previous Use of OGS Apps

Table 5: Multiple Linear Regression: Quality of the Models; N = 181.

| Hypotheses                              | Path Coefficient | Standard<br>Error | Result       |  |
|---|------------------|-------------------|--------------|--|
| H01 PE → BI                             | 0.493***         | 0.071             | ✓            |  |
| H02 EE $\rightarrow$ BI                 | -0.012           | 0.073             | X            |  |
| $H03 SI \rightarrow BI$                 | -0.008           | 0.062             | X            |  |
| $H04 FC \rightarrow BI$                 | 0.019            | 0.061             | X            |  |
| H05 $HM \rightarrow BI$                 | 0.142**          | 0.070             | $\checkmark$ |  |
| $H06 \text{ PV} \rightarrow BI$         | 0.009            | 0.075             | X            |  |
| H07 HA $\rightarrow$ BI                 | 0.086            | 0.082             | X            |  |
| ${\text{Gender} \rightarrow \text{BI}}$ | 0.049            | 0.172             |              |  |
| Age → BI                                | 0.013            | 0.008             | X            |  |
| Previous Use of OGS Apps →BI            | 0.329***         | 0.101             | <i>X</i> ✓   |  |

Note: Significance level: \* p < 0.05; \*\*\* p < 0.01; \*\*\* p < 0.001

Table 6: Model Results and Testing of Hypotheses; N = 181

<sup>&</sup>lt;sup>b</sup> Model (1): Predictors = Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value and Habit

 $<sup>^{\</sup>rm c}$  Model (2): Predictors = Gender, Age, Previous Use of OGS Apps, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value and Habit  $R^2$  = Coefficient determination; \*\*\* = Significance of the change [p = 0.001]

Table 6 illustrates that only hypotheses H01 (performance expectation) and H05 (hedonic motivation) positively influenced BI to use OGS apps. The influence of PE on BI was dominant, with a correlation coefficient of 0.493. This significant positive influence was followed by the control variable previous use of OGS apps, which had a correlation coefficient of 0.329 and was also highly significantly related to BI. Additionally, HM remained a significant predictor of the future use of OGS apps in our study, with a correlation coefficient of 0.142. The remaining predictors of the UTAUT2 model and the control variables, age and gender, could not be proven to be significant estimation parameters in the model. Consequently, these hypotheses had to be rejected.

# 6. Discussion and Implications for Theory and Practice

This study explored the acceptance and usage patterns of OGS apps in Germany, utilizing the UTAUT2 model to identify key factors influencing user intentions and behavior. This study answers a direct call for future research addressed in Leischner (2023), as the authors posit that OGS in Germany still has a considerable amount of untapped potential, especially with regard to convenience and stress reduction when shopping online. Our study showed that the UTAUT2 model provided a solid framework for understanding the acceptance and usage patterns of OGS apps in Germany. Statistical analysis, including MLPCA and MLR, validated the reliability and accuracy of the constructs that were measured, reinforcing the robustness of the UTAUT2 model. Second, the primary factors influencing the intention to use OGS apps were identified. Performance expectancy (PE), hedonic motivation (HM), and prior use of OGS apps were found to exert the most significant impact. This suggests that users prioritize functional benefits and seek enjoyment and familiarity when engaging with OGS apps, which aligns with the findings from Rudolph et al. (2015). Hedonic motivation is crucial in driving app engagement and sustained use by emphasizing the importance of enjoyment and pleasure. Consequently, users are seeking an experience that is both practical and entertaining. The preference for established retail brands highlights the competitive advantage of traditional retailers in this market. The results of this study provide a clear basis for action for delivery services in the OGS sector in Germany. By considering the challenges of OGS apps and implementing the suggested measures, providers can optimize and increase acceptance of their services.

# Theoretical Implications

The study has important theoretical implications for the development of digital services. It highlights the relevance of the UTAUT2 model in understanding consumer behavior relative to OGS apps, emphasizing the importance of PE, EE, and HM. The findings suggest that the UTAUT2 model and the questionnaire need to be adapted to the specifics of OGS applications to accurately represent user perceptions and behaviors. The findings of this study align with previous research that emphasized the importance of PE and HM in technology acceptance (Venkatesh et al., 2012). However, this study extends the existing literature by highlighting the significant role of previous usage behavior, which was less explored in prior research. The emphasis on targeted marketing strategies for repeat customers and operationalizing performance expectations and hedonic motives through user-friendly design and clear value propositions offer new insights to researchers and practitioners. This research also supports the findings of Harborth and Pape (2018), who highlighted the importance of cultural context in technology acceptance. This suggests that future studies should continue to explore cross-cultural differences to gain a more nuanced understanding of user behaviors (Netscher et al., 2024).

### Practical Implications

For practice, we suggest focusing the marketing of OGS apps on prior usage behavior, performance expectations, and hedonic motivations. First, it is easier to encourage repeat customers than new customers to use the app, given that they have already had positive experiences with it. Therefore, targeted campaigns should be developed to retain customers and encourage repeat purchases. Second,

PE and HM should be operationalized through a user-friendly design and by adding clear value to the app. If the app is both functionally convincing and enjoyable to use, willingness to use it can be significantly increased. Marketing measures should, therefore, focus on improving the user experience and communicating the added value to increase user satisfaction and loyalty.

### 7. Conclusion and Future Research

The study on OGS apps in Germany provides valuable insights into user acceptance and usage patterns. In conclusion, this study offers valuable insights for both researchers and practitioners in the field of digital services. OGS app providers can optimize their services and increase both user adoption and acceptance by addressing the specific challenges in rural areas and implementing targeted marketing strategies. However, it is important to expand the research scope to include sustainability aspects and potential adverse effects of OGS, which are currently under-explored (Chan et al., 2023) and were not part of this study. Another limitation of this study is the small sample size of 181 participants, which may limit the generalizability of the findings. Additionally, the sample was recruited through social media platforms, potentially biasing the results as not all demographic groups are equally represented. Geographically, the study focuses exclusively on Germany, meaning that the results may not directly apply to other countries or cultures. Additionally, future studies should focus on rural areas and the need for improved logistics and infrastructure.

The data collection was performed over a limited period, from November to December 2023. Consequently, no changes in technology or user behavior that occurred after this period were considered. The reliance on self-reported data introduces the possibility of biases such as social desirability or recall errors that could affect the accuracy of the results. While the UTAUT2 model provided a robust framework for analysis, other theoretical models or additional variables might also be relevant to fully understanding the acceptance and use of OGS apps. Moreover, the study examines the intention to use OGS apps but does not provide a long-term perspective on actual usage behavior and user retention. Focusing on specific predictors such as PE and HM meant that other potentially relevant factors—for example, technological advancements or market trends, like sustainability—were not considered. These limitations provide a framework for future research that could expand and deepen the insights gained from this study. Future research should examine the role of OGS apps in promoting sustainable consumption patterns and supporting local food systems. Future studies can provide a more comprehensive understanding of the complex implications of OGS adoption, balancing technological advancements with sustainability concerns and potential negative societal impacts.

# References and notes

- Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management*, 37(3), 99–110. https://doi.org/10.1016/j.ijinfomgt.2017.01.002
- Al-nawayseh, M. K., Alnabhan, M. M., Al-Debei, M. M., & Balachandran, W. (2013). An Adaptive Decision Support System for Last Mile Logistics in E-Commerce: A Study on Online Grocery Shopping. *International Journal of Decision Support System Technology (IJDSST)*, 5(1), 40–65. https://doi.org/10.4018/jdsst.2013010103
- Asgari, H., Azimi, G., Titiloye, I., & Jin, X. (2023). Exploring the influences of personal attitudes on the intention of continuing online grocery shopping after the COVID-19 pandemic. *Travel Behaviour and Society, 33*, 100622. https://doi.org/10.1016/j.tbs.2023.100622
- Backhaus, K., Erichson, B., & Weiber, R. (2015). Fortgeschrittene Multivariate Analysemethoden: Eine anwendungsorientierte Einführung (3., überarb. u. aktual. Aufl. 2015). Gabler.
- Braun, S., & Osman, D. (2024). Online grocery shopping adoption versus non-adoption among the over-50s in Germany. *Electronic Commerce Research*, *24*(2), 825–862. https://doi.org/10.1007/s10660-024-09840-7
- Brown, S. A., & Venkatesh, V. (2005). Model of Adoption of Technology in Households: A Baseline Model Test and Extension Incorporating Household Life Cycle. *MIS Quarterly*, 29(3), 399–426. https://doi.org/10.2307/25148690
- Brüggemann, P., Martinez, L. F., Pauwels, K., & Westland, J. C. (2024). Introduction: Online grocery shopping current and future challenges and opportunities. *Electronic Commerce Research*, 24(2), 711–713. https://doi.org/10.1007/s10660-024-09875-w
- Bundesverband E-Commerce und Versandhandel Deutschland (BEVH) e.V. (2024). *Umsatz mit Lebensmitteln im deutschen Online-Handel bis 2024*. Statista. https://de.statista.com/statistik/daten/studie/894997/umfrage/umsatz-mit-lebensmitteln-im-deutschen-online-handel/
- Chan, H.-L., Cheung, T.-T., Choi, T.-M., & Sheu, J.-B. (2023). Sustainable successes in third-party food delivery operations in the digital platform era. Annals of Operations Research, 1–37. https://doi.org/10.1007/s10479-023-05266-w

- Cleff, T. (2015). Deskriptive Statistik und Explorative Datenanalyse: Eine computergestützte Einführung mit Excel, SPSS und STATA (3., überarbeitete und ergänzte Auflage). Springer Gabler.
- Deaux, K., & Lewis, L. L. (1984). Structure of gender stereotypes: Interrelationships among components and gender label. *Journal of Personality and Social Psychology*, 46(5), 991–1004. https://doi.org/10.1037/0022-3514.46.5.991
- Dillahunt, T. R., Simioni, S., & Xu, X. (2019). Online Grocery Delivery Services: An Opportunity to Address Food Disparities in Transportationscarce Areas. *Proceedings of the 2019 CHI Conference* on Human Factors in Computing Systems, 1–15. https://doi.org/10.1145/3290605.3300879
- Driediger, F., & Bhatiasevi, V. (2019). Online grocery shopping in Thailand: Consumer acceptance and usage behavior. *Journal of Retailing and Consumer Services*, 48, 224–237. https://doi.org/10.1016/j.jretconser.2019.02.005
- Frank, D.-A., & Peschel, A. O. (2020). Sweetening the Deal: The Ingredients that Drive Consumer Adoption of Online Grocery Shopping. *Journal of Food Products Marketing*, 26(8), 535–544. https://doi.org/10.1080/10454446.2020.1829523
- Gillespie, R., DeWitt, E., Trude, A. C. B., Haynes-Maslow, L., Hudson, T., Anderson-Steeves, E., Barr, M., & Gustafson, A. (2022). Barriers and Facilitators of Online Grocery Services: Perceptions from Rural and Urban Grocery Store Managers. *Nutrients*, 14(18), Article 18. https://doi.org/10.3390/nu14183794
- Gruntkowski, L. M., & Martinez, L. F. (2022). Online Grocery Shopping in Germany: Assessing the Impact of COVID-19. *Journal of Theoretical and Applied Electronic Commerce Research*, 17(3), Article 3. https://doi.org/10.3390/jtaer17030050
- Gupta, U., & Kumar, N. (2023). Analysing the Impact of Perceived Risk, Trust and Past Purchase Satisfaction on Repurchase Intentions in Case of Online Grocery Shopping in India. Global Business Review. https://doi.org/10.1177/09721509231178989
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). SAGE.

- Handelsverband Deutschland (HDE) e.V. (2024).

  Anteil des Online-Umsatzes mit Lebensmitteln am
  Einzelhandelsumsatz in Deutschland in den Jahren 2014
  bis 2023. Statista. https://de.statista.com/statistik/daten/
  studie/744285/umfrage/onlineanteil-von-lebensmittelnam-einzelhandel-in-deutschland/
- Hansson, L., Holmberg, U., & Post, A. (2022). Reorganising grocery shopping practices the case of elderly consumers. *The International Review of Retail, Distribution and Consumer Research*, *32*(4), 351–369. https://doi.org/10.1080/09593969.2022.2085137
- Harborth, D., & Pape, S. (2018). German Translation of the
  Unified Theory of Acceptance and Use of Technology
  2 (UTAUT2) Questionnaire (SSRN Scholarly
  Paper 3147708). Social Science Research Network.
  https://doi.org/10.2139/ssrn.3147708
- Hartmann, T., & Reinecke, L. (2013). Skalenkonstruktion in der Kommunikationswissenschaft (pp. 41–60). https://doi.org/10.1007/978-3-531-18776-1 3
- Hassan, S., Rashid, R., & Li, F. (2015). Utilising Modified UTAUT to Understand Students' Online Shopping Behaviour: A Case of E-Retail Co-Operative Website in Malaysia. *Journal of Electronic Commerce in Organizations (JECO)*, 13(4), 74–90. https://doi.org/10.4018/JECO.2015100104
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A New Criterion for Assessing Discriminant Validity in Variance-based Structural Equation Modeling. *Journal of the Academy of Marketing Science*, 43, 115–135. https://doi.org/10.1007/s11747-014-0403-8
- Indrawati, I., Ramantoko, G., Widarmanti, T., Aziz, I. A., & Khan, F. U. (2022). Utilitarian, hedonic, and self-esteem motives in online shopping. Spanish Journal of Marketing ESIC, 26(2), 231–246. https://doi.org/10.1108/SJME-06-2021-0113
- Johnson, R. A., & Wichern, D. W. (2007). *Applied Multivariate Statistical Analysis: International Edition* (6th edition). Pearson.
- Klepek, M., & Bauerová, R. (2020). Why do retail customers hesitate for shopping grocery online? *Technological and Economic Development of Economy*, 26(6), Article 6. https://doi.org/10.3846/tede.2020.13970
- Kvalsvik, F. (2022). Understanding the role of situational factors on online grocery shopping among older adults. *Journal of Retailing and Consumer Services*, 68, 103009. https://doi.org/10.1016/j.jretconser.2022.103009

- Lee, M.-C. (2009). Factors influencing the adoption of internet banking: An integration of TAM and TPB with perceived risk and perceived benefit. *Electronic Commerce Research and Applications*, 8(3), 130–141. https://doi.org/10.1016/j.elerap.2008.11.006
- Leischner, E. (2023). Online-Lebensmittelhandel in Deutschland–Kundenseite. In *Online-Lebensmittelhandel in Deutschland* (pp. 69–82). Springer Gabler, Wiesbaden. https://doi.org/10.1007/978-3-658-42210-3\_4
- Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance. *MIS Quarterly*, 31(4), 705–737. https://doi.org/10.2307/25148817
- Liu, Y., Wang, M., Huang, D., Huang, Q., Yang, H., & Li, Z. (2019). The impact of mobility, risk, and cost on the users' intention to adopt mobile payments. *Information Systems and E-Business Management*, 17(2), 319–342. https://doi.org/10.1007/s10257-019-00449-0
- Monoarfa, T. A., Sumarwan, U., Suroso, A. I., & Wulandari, R. (2024). Uncover the trends, gaps, and main topics on online grocery shopping: Bibliometric analysis. *Heliyon*, 10(4). https://doi.org/10.1016/j.heliyon.2024.e25857
- Morris, M., Schindehutte, M., & Allen, J. (2005). The entrepreneur's business model: Toward a unified perspective. *Journal of Business Research*, 58(6), 726– 735. https://doi.org/10.1016/j.jbusres.2003.11.001
- Musakwa, I. S., & Petersen, F. (2023). Factors affecting consumer acceptance and use of mobile delivery applications in South Africa. South African Journal of Information Management, 25(1), Article 1. https://doi.org/10.4102/sajim.v25i1.1585
- Musikavanhu, T. B., & Musakuro, R. N. (2023).
  Consumer adoption of online grocery shopping in South Africa. South African Journal of Information Management, 25(1), Article 1. https://doi.org/10.4102/sajim.v25i1.1637
- Netscher, M., Jordan, S., & Kracklauer, A. H. (2025). Exploring Customer Acceptance of Smart Stores: An Advanced Model Approach. In M. A. Bach Tobji, R. Jallouli, H. Sadok, K. Lajfari, D. Mafamane, & H. Mahboub (Eds.), Digital Economy. Emerging Technologies and Business Innovation (pp. 311–338). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-76365-6\_19

- Park, D.-H., Lee, J., & Han, I. (2007). The Effect of On-Line Consumer Reviews on Consumer Purchasing Intention: The Moderating Role of Involvement. *International Journal of Electronic Commerce*, 11(4), 125–148. https://doi.org/10.2753/JEC1086-4415110405
- Qazi, A., Hasan, N., Abayomi-Alli, O., Hardaker, G., Scherer, R., Sarker, Y., Kumar Paul, S., & Maitama, J. Z. (2022). Gender differences in information and communication technology use & skills: A systematic review and meta-analysis. *Education* and Information Technologies, 27(3), 4225–4258. https://doi.org/10.1007/s10639-021-10775-x
- Rakhman, R. T., Piliang, Y. A., Ahmad, H. A., & Gunawan, I. (2021). Representation of Digital Native Generation in Visual Images. Arts and Design Studies, 90(0), 18–23. https://iiste.org/Journals/index.php/ADS/article/ view/55523
- Rudolph, T., Nagengast, L., Bassett, M., & Bouteiller, D. (2015). Die Nutzung mobiler Shopping Apps im Kaufprozess. *Marketing Review St. Gallen*, 32(3), 42–49. https://doi.org/10.1007/s11621-015-0529-1
- Shen, H., Namdarpour, F., & Lin, J. (2022). Investigation of online grocery shopping and delivery preference before, during, and after COVID-19. *Transportation Research Interdisciplinary Perspectives*, 14, 100580. https://doi.org/10.1016/j.trip.2022.100580
- Shroff, A., Kumar, S., Martinez, L. M., & Pandey, N. (2024). From clicks to consequences: A multimethod review of online grocery shopping. *Electronic Commerce Research*, 24(2), 925–964. https://doi.org/10.1007/s10660-023-09761-x
- Singh, R., & Söderlund, M. (2020). Extending the experience construct: An examination of online grocery shopping. *European Journal of Marketing, ahead-of-print*. https://doi.org/10.1108/EJM-06-2019-0536
- Tabachnick, B. G., & Fidell, L. S. (2014). Using multivariate statistics (Sixth edition, Pearson new international edition). Pearson.
- Taglinger, M., Jordan, S., & Kracklauer, A. H. (2023).
  Acceptance of Artificially Intelligent Digital Humans in Online Shops: A modelling approach. *Journal of Applied Interdisciplinary Research*, *I*, Article 1. https://doi.org/10.25929/jair.v1i1.127
- Thong, J., Hong, S.-J., & Tam, K. (2006). The effects of post-adoption be-liefs on the expectation-confirmation model

- for information technology continuance. International Journal of Human Computer Studies, 64(9), 799-810. *International Journal of Human-Computer Studies*, 64, 799–810. https://doi.org/10.1016/j.ijhcs.2006.05.001
- Venkatesh, V. (2006). Where To Go From Here? Thoughts on Future Directions for Research on Individual-Level Technology Adoption with a Focus on Decision Making. *Decision Sciences*, 37(4), 497–518. https://doi.org/10.1111/j.1540-5414.2006.00136.x
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540
- Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly, 36, 157–178. https://doi.org/10.2307/41410412
- Verhoef, P., & Langerak, F. (2001). Possible Determinants of Consumers' Adoption of Electronic Grocery Shopping in the Netherlands. *Journal of Retailing and Consumer Services*, 8, 275–285. https://doi.org/10.1016/S0969-6989(00)00033-3
- Yim, M. Y.-C., Yoo, S.-C., Sauer, P. L., & Seo, J. H. (2014). Hedonic shopping motivation and co-shopper influence on utilitarian grocery shopping in superstores. *Journal* of the Academy of Marketing Science, 42(5), 528–544. https://doi.org/10.1007/s11747-013-0357-2
- Younes, H., Noland, R. B., & Zhang, W. (2022). Browsing for food: Will COVID-induced online grocery delivery persist? *Regional Science Policy & Practice*, 14, 179– 196. https://doi.org/10.1111/rsp3.12542
- Yu, E. (2010). Modeling Strategic Relationships for Process Reengineering. https://doi.org/10.7551/mitpress/7549.003.0005
- Zeithaml, V. (1988). Consumer Perceptions of Price, Quality and Value: A Means-End Model and Synthesis of Evidence. *Journal of Marketing*, 52, 2–22. https://doi.org/10.1177/002224298805200302
- Zolfaghari, A., Thomas-Francois, K., & Somogyi, S. (2022).
  Consumer adoption of digital grocery shopping:
  What is the impact of consumer's prior-to-use knowledge? *British Food Journal*, 125(4), 1355–1373. https://doi.org/10.1108/BFJ-02-2022-0187

# **Appendix**

A. 1: QR Code and Link for the Self-created explanatory video that introduced the topic to the participants



Figure 4: QR code for the explanatory video.

Link for the explanatory video:

https://drive.google.com/file/d/1-KDvolA\_mlIWIs\_-FckxUdzdkZNQ5vJ6/view?usp=sharing