Social Science Studies
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Adoption of QR Code Menu for Making Order: An Extended UTAUT2 Approach

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ARTICLE INFO	ABSTRACT

ISSN: 2798-2688

Research Aims: This study aims to test the adoption of QR code menus model that incorporate the concept of epistemic value in the UTAUT2 model, in the context of metropolitan cafés in Indonesia.

Design/methodology/approach: This study employed a quantitative approach. Data were collected from 206 respondents through a purposive sampling strategy. The analysis was conducted using the Partial Least Square Structural Equation Modeling (PLS-SEM) method with the SmartPLS 4.0 software.

Research Findings: The adoption of QR code menus is significantly driven by several key factors. Effort expectancy, social influence, habit, and epistemic value all play a significant role in motivating individuals to use this technology. However, performance expectancy and facilitating condition do not have a significant impact on adoption. This suggests that while ease of use, social acceptance, routine behavior, and a desire for novelty are crucial, the perceived benefits and availability of supporting resources are not primary motivators for use.

Theoretical Contribution/Originality: This study offers empirical evidence of the implementation of extended UTAUT2 in the specific contexts of behavioral intention and usage of QR code menus in Indonesian metropolitan café. Although prior studies have examined the advantages of digital menus in the food and beverage industry, limited attention has been given to the behavioral intentions of metropolitan café customers in Indonesia toward QR code menus. This study addresses that gap by integrating epistemic value (the desire for novelty, knowledge, and exploration) into the adoption model, offering a unique perspective within the Indonesian context where QR code menus are still relatively new and continue to shape customer experiences.

Keywords*:* QR Code Menu, UTAUT2, Behavioral Intention, Use Behavior, Epistemic Value.

Social Science Studies Vol. 5 No. 5 2025 Page 413-437
DOI: 10.47153/sss55.20932025
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Introduction

The global food and beverage (F&B) sector has been undergoing a profound digital transformation, with technological innovations like mobile applications, self-service kiosks, and online ordering platforms becoming indispensable for enhancing operational efficiency and customer service (Koay & Ang, 2024). The COVID-19 pandemic significantly accelerated the digital shift, driving the rapid adoption of contactless technologies, such as QR code menus. This was necessary to reduce physical contact and adhere to public health guidelines (Brewer & Sebby, 2021). This unprecedented global event served as a powerful catalyst, compelling businesses worldwide to embrace technologies that would have otherwise taken significantly longer to integrate (Chan, 2023).

In urban settings where contactless service is favored, QR code menus have become very popular. By scanning a two-dimensional barcode with their smartphones, customers can view a digital menu without needing a physical one (Ozturkcan & Kitapci, 2023). This technology swiftly emerged as a critical tool during the pandemic, improving operational efficiency and ensuring customer safety. As businesses continue to advance into the digital age, QR code menus are solidifying their position as a common feature in contemporary cafés, particularly in technologically advanced urban areas (Ozturkcan & Kitapci, 2023).

Greater Jakarta, Indonesia's most significant urban agglomeration, serves as the nation's economic and business hub, a focal point for innovation and technological advancement (Sofa, 2024). Its rapid urbanization and digital evolution create an ideal setting for examining the adoption of digital technologies within the F&B sector. Furthermore, data from BPS-Statistics Indonesia (2023) highlights a substantial proportion of dine-in customers in Greater Jakarta, making it a prime location to study the implementation of QR code menus. Specifically, 52.82% of orders in the DKI Jakarta region and 48.76% in West Java (which includes parts of Greater Jakarta) are consumed on-site. The data highlights that a substantial number of customer interactions in cafés occur through direct, on-site consumption. In these scenarios, digital solutions like QR code menus can be particularly effective in improving the customer experience and streamlining operational efficiency. The proliferation of cafés and restaurants in Greater Jakarta further emphasizes the relevance of this study, as businesses increasingly embrace digital ordering systems to optimize processes, minimize wait times, and improve overall dining experiences (Nikose, Hatwar, Nikose, Adikane, & Gaharwar, 2023). The intense competition within the F&B industry in this region accentuates the need for innovative solutions, such as QR code menus, to align with evolving customer expectations and enhance operational efficiency (Koay & Ang, 2024).

QR code menus offer numerous advantages for both cafés and their patrons. For cafés, they notably improve operational efficiency by reducing waiting times, allowing customers to place orders directly, and consequently increasing the number of customers served, potentially leading to higher revenue (Popescu & Neacşu, 2024). Additionally, QR code menus minimize order errors, significantly boosting customer satisfaction (Kimes & Laqué, 2011). Digital menus also offer a more economical solution than traditional printed menus, allowing for real-time updates without reprinting. This adaptability is crucial for businesses in the fast-paced F&B industry, where consumer preferences can shift rapidly (Ozkaya, Ozkaya, Roxas, Bryant, & Whitson, 2015; Pandey, 2023). Customers benefit from the convenience and interactivity of digital menus, often featuring high-quality images, nutritional information, and customization options, enriching their overall dining experience (Şahin, 2020).

Despite these clear advantages, the implementation of QR code menus in Indonesia has encountered challenges. A primary obstacle is customer hesitation to deviate from conventional ordering methods. Some customers, particularly those less tech-savvy, may prefer physical menus or direct interaction with servers over using a QR code (Koay & Ang, 2024). This highlights the critical need to understand the behavioral intentions of café patrons in Indonesia, as the effectiveness of QR code menus hinges not solely on the technology itself, but on customers' readiness to adopt it.

This research employs the UTAUT2 model (Unified Theory of Acceptance and Use of Technology 2), developed by Venkatesh et al. (2012), as its foundational framework. The UTAUT2 model expands upon the original UTAUT model by adding several constructs pertinent to consumer settings, such as hedonic motivation, price value, and habit. However, in this study, hedonic motivation and price value are excluded from the research model. This is because their influence on QR code menu adoption is anticipated to be minimal, as the adoption is driven more by efficiency and convenience rather than pleasure or a direct financial cost to the customer (Iskender, Sirakaya-Turk, & Cardenas, 2023; Koay & Ang, 2024). Customers are primarily driven by efficiency and reduced physical interaction, not enjoyment from the technology itself. For QR code menus, the direct financial cost to the customer is typically negligible, since cafés do not usually charge a fee for this service. Instead, the businesses bear the costs of implementation and maintenance. As a result, the price value of the technology is not a significant factor in shaping customers' behavioral intentions.

While previous research has explored the benefits of digital menus in the F&B sector (e.g., Koay & Ang, 2024; Popescu & Neacșu, 2024). However, a notable gap persists in the literature concerning the specific behavioral intentions of Indonesian metropolitan café customers regarding QR code menus. While many studies have broadly explored technology adoption in consumer settings, a direct application to this niche and geographical context is limited. For instance, while Venkatesh et al. (2012) developed the UTAUT2 model developed for consumer technology adoption, has not been extensively applied to QR code menus in Indonesian cafés, especially with the integrated construct of epistemic value. Furthermore, existing research, such as that by Iskender et al., (2022), might touch upon digital menu use, but often without the nuanced behavioral framework or the specific cultural and technological landscape of Indonesia. This study seeks to fill a research gap by investigating the factors that influence customer behavioral intentions and the actual use of QR code menus in cafés located in urban areas such as Greater Jakarta.

In order to conduct a more thorough analysis, this study incorporates the concept of epistemic value from the Theory of Consumption Value (Sheth, Newman, & Gross, 1991). Epistemic value is defined as the perceived benefit gained from an alternative's capacity to stimulate curiosity, provide novelty, and satisfy a desire for knowledge. The use of QR code menus represents a novel technological advancement that is likely to appeal to customers seeking cutting-edge dining experiences. Cafés adopting QR code menus may be perceived as technologically forward-thinking within the evolving F&B industry, thereby enhancing their appeal to tech-savvy customers. The understanding of factors that influence the adoption of QR code menus among café customers in Greater Jakarta can be improved by integrating the concept of epistemic value into the UTAUT2 model, as suggested by Ong et al. (2023).

This research aims to test an adoption model for QR code menus that integrates the concept of epistemic value into the UTAUT2 framework, specifically within Indonesian cafés. By concentrating on customers in Greater Jakarta, this study will provide valuable insights into how urban consumers in Indonesia perceive and use digital menus, along with the factors influencing their decision to adopt or reject the technology. As digital solutions become more significant in the F&B sector, understanding these factors is essential for cafés to stay competitive and meet evolving customer demands.

Literature Review

QR Code Menu

The QR Code Menu represents a cutting-edge use of QR code technology, mainly employed in the food service sector to improve customer satisfaction and streamline operations. According to Hughes (2016), operational systems are those needed to execute daily commercial transactions and subsequent data processing to complete business obligations, often called transaction capture systems or online transaction processing (OLTP) applications. QR codes, as advanced barcodes that hold large information volumes, perfectly embody this operational system function by enabling users to swiftly access digital content through smartphone scanning (Iskender et al., 2023; Koay & Ang, 2024). This technology has become increasingly popular post-pandemic as it provides contactless menu access, addressing health concerns with shared physical menus while processing business transactions efficiently.

Unified Theory of Acceptance and Use Technology 2 (UTAUT2)

Developed in 2003, the Unified Theory of Acceptance and Use of Technology (UTAUT) is a model for understanding technology adoption that accounts for significant variance in usage behavior. Its central components are Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Condition. The model was later refined into UTAUT2 in 2012 by Venkatesh, Thong, and Xu, specifically for consumer contexts. A key distinction is that in UTAUT2, the influence of behavioral intention on technology usage is moderated by user experience. This updated version notably increased the explained variance for behavioral intention (from 56% to 74%) and technology use (from 40% to 52%) compared to the original UTAUT model. UTAUT2 also introduced three new constructs: Hedonic Motivation, Price Value, and Habit. For this study, Hedonic Motivation is excluded because of its minimal impact on behavioral intention for QR code menus (Koay & Ang, 2024), and Price Value is also excluded since customers do not incur a direct financial cost for using this technology (Iskender et al., 2022).

Performance Expectancy (PE) and Behavioral Intention (BI)

Performance Expectancy is the belief that a system will improve an individual's performance or ability to execute specific tasks (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh et al., 2012). This factor is a significant predictor of behavioral intention and is often considered the most critical influence on new technology adoption (Venkatesh et al., 2003, 2012). In the context of QR code menus, a customer's attitude and intentions are strongly shaped by their performance expectancy. Customers are more inclined to use QR code menus if they believe it will simplify the ordering process, enhance their dining experience, or provide more detailed menu information (Koay & Ang, 2024). The expectation of greater service efficiency and convenience significantly increases the likelihood of adopting QR code menus, particularly in a post-pandemic environment where contactless solutions are preferred (Koay & Ang, 2024).

H1: Performance Expectancy (PE) significantly affects Behavioral Intention (BI)

Effort Expectancy (EE) and Behavioral Intention (BI)

Effort Expectancy is a key concept that refers to the perceived ease of using a new system or technology (Venkatesh et al., 2003, 2012). This concept is a crucial predictor of a user's behavioral intention and technology adoption. It is rooted in other models, such as the Technology Acceptance Model (TAM), the Model of Personal Computer Utilization (MPCU), and the Innovation Diffusion Theory (IDT). For example, user-friendly mobile applications that require less effort tend to have much higher adoption rates (Park & Ohm, 2014). In essence, when a new technology is straightforward to learn and understand, people are far more likely to embrace it (Chua, Rezaei, Gu, Oh, & Jambulingam, 2018).

H2: Effort Expectancy (EE) significantly affects Behavioral Intention (BI)

Social Influence (SI) and Behavioral Intention (BI)

Within the context of technology acceptance, Social Influence is defined as the degree to which individuals perceive that significant people in their lives, such as family, friends, or colleagues, expect them to adopt a particular technology (Venkatesh et al., 2003). As a crucial component of the UTAUT model, it highlights how social norms and peer endorsement can significantly shape an individual's intention to embrace new technologies (Venkatesh et al., 2003). Individuals are more inclined to use technology when they feel that their peers support such behaviors, particularly in settings where technology adoption is widespread, which creates a normative influence. This concept aligns with Gumasing et al. (2022) observations from research on behavioral intentions toward online grocery applications during the COVID-19 pandemic.

H3: Social Influence (SI) significantly affects Behavioral Intention (BI)

Facilitating Condition (FC) and Behavioral Intention (BI)

Facilitating Condition refers to the degree to which individuals believe that the necessary organizational and technical infrastructure exists to support technology use (Venkatesh et al., 2003, 2012). This includes readily available resources, technical support, and training, all of which are crucial for users to proficiently interact with a system (Venkatesh et al., 2012). This construct significantly influences behavioral intention, as a user's intention to adopt technology increases when they perceive robust facilitating conditions (Bile Hassan, Murad, El-Shekeil, & Liu, 2022). For example, in digital payment or cloud-based quality management systems, adequate facilitating conditions lead to improved behavioral intentions (Ong et al., 2023). Empirical evidence consistently shows that facilitating conditions impact behavioral, as seen in the realm of health information applications (Bile Hassan et al., 2022).

H4: Facilitating Condition (FC) significantly affects Behavioral Intention (BI)

Habit (HT) and Behavioral Intention (BI)

Within the UTAUT2 framework, habit is the degree to which individuals perform technology-related behaviors automatically as a result of previous experience. This suggests that the use of technology can become an integrated, almost effortless part of a person's daily routine (Venkatesh et al., 2012). This concept highlights how technology use can become seamlessly integrated into daily routines, making interaction more automatic and less reliant on conscious decisions (Gumasing et al., 2022). Habit significantly influences behavioral intention. Research consistently shows that as users develop habitual behaviors with a technology, their dependence on it increases, leading to more regular and frequent use (Gumasing et al., 2022; Martinez & McAndrews, 2023; Romero-Rodríguez, Ramírez-Montoya, Buenestado-Fernández, & Lara-Lara, 2023).

H5: Habit (HT) significantly affects Behavioral Intention (BI)

Epistemic Value (EV) and Behavioral Intention (BI)

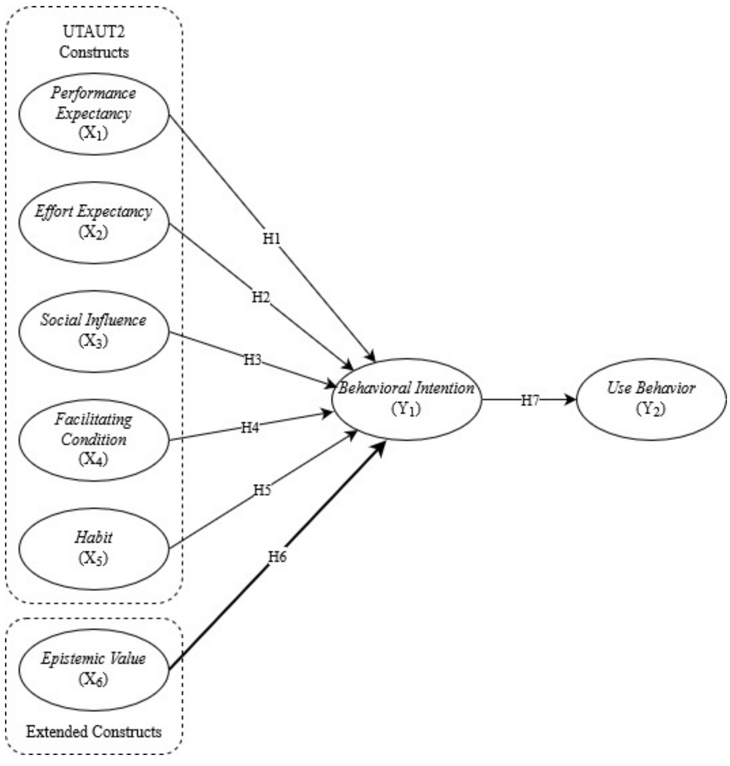
Based on the Theory of Consumption Values by Sheth et al. (1991), Epistemic Value is the perceived benefit gained from a product or service's ability to spark curiosity and fulfill a desire for knowledge. In this study, it measures respondents' perceptions of the QR code menu's capacity to evoke curiosity, provide new experiences, and fulfill knowledge needs through innovative or interactive features. Integrating Epistemic Value into the UTAUT2 model addresses the model's limited coverage of psychological motivations like curiosity, which can drive technology adoption, especially for unfamiliar users. This theoretical framework posits that consumers derive satisfaction from learning and exploration, enhancing their understanding of products and services, aligning with studies emphasizing intrinsic motivation in product search behavior. Ong et al. (2023) demonstrates that Epistemic Value significantly influences behavioral intention, indicating users are motivated by the desire for novel features or unique experiences in digital payment systems. By including Epistemic Value, this study extends beyond practical factors to highlight intrinsic motivation's role in technology acceptance, offering a comprehensive understanding of QR code menu adoption.

H6: Epistemic Value (EV) significantly affects Behavioral Intention (BI)

Behavioral Intention (BI) and Use Behavior (UB)

Behavioral intention, as defined by Venkatesh et al. (2003, 2016, 2012), represents an individual's conscious plan or preparedness to engage in a specific technology-related behavior. It is a direct precursor to actual technology use, highlighting its crucial role in the adoption process (Venkatesh et al., 2003, 2012). The significant influence of behavioral intention on actual technology usage is a well-established phenomenon, widely documented in the literature. Multiple studies confirm that a strong behavioral intention serves as a powerful predictor of actual technology use, resulting in higher adoption rates across various contexts, such as online grocery shopping and digital payment systems (Gumasing et al., 2022; Ong et al., 2023). Use behavior, as defined by Venkatesh et al. (2003, 2016, 2012), represents the extent to which a person actively engages with a technology. The UTAUT2 model specifically aims to predict and explain this ultimate outcome: genuine interaction with technology (Venkatesh et al., 2016, 2012). The strong link between use behavior and its antecedents is well-established grounded in UTAUT2 and the hypotheses model can be seen in Figure 1.

Figure 1. Hypothesis Model



Method

This study is quantitative explanatory research aimed at explaining the causal relationships between variables. The quantitative method was chosen to objectively evaluate hypotheses and analyze numerical data. The variables were adapted from the research by Ong et al.'s (2023) on digital payment adoption, which extended the UTAUT2 model with Consumption Value Theory. The sampling method used was non-probability sampling, specifically a purposive sampling strategy. The established criteria for participants included having used a QR code menu at least once in the last six months, using it in cafés throughout Greater Jakarta, using a smartphone to access it, and being at least 18 years old. The minimum sample size required was 160 respondents, calculated using the formula by Memon et al. (2020). A total of 206 respondents who met the criteria were obtained. Data collection was conducted through an online questionnaire using Google Forms. The questionnaire link was distributed individually to café customers in Greater Jakarta via electronic channels like X, WhatsApp, Line, and Instagram. The first page of the questionnaire outlined the respondent criteria, and only those who met them were required to continue. Google Forms "required" feature ensured that participants had to answer every question, guaranteeing data accuracy

This study uses Partial Least Square Structural Equation Modeling (PLS-SEM) for data analysis. PLS-SEM is a powerful multivariate technique that combines factor analysis and multiple regression, allowing for the simultaneous analysis of complex relationships between variables (Hair, Hult, Ringle, & Sarstedt, 2022). This approach is especially effective for research that aims to predict and validate relationships within a theoretical model. All calculations for this study were performed using the SmartPLS version 4.0 software. The evaluation of the PLS-SEM model consists of two key stages: the outer model and the inner model. The outer model (measurement model) assesses the validity and reliability of the research model by examining the relationships between latent variables and their indicators. This stage evaluates indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The inner model (structural model) outlines the relationships between the latent variables themselves, based on the study's theoretical framework. This model is crucial for analyzing causal relationships and assessing the model's predictive capabilities. Its evaluation involves testing the Variance Inflation Factor (VIF), path coefficients, the coefficient of determination (R^2), and predictive power (Hair et al., 2022).

Result and Discussion

The description of respondents in this study is differentiated based on gender, age, domicile, occupation, last education level, frequency of visiting cafés, and monthly income. This study included 206 respondents, with near gender parity (50.49% male, 49.51% female). The majority were young adults aged 20-21 (47.57%), residing primarily in Jakarta (36.98%). Most respondents were students (91.26%) with bachelor's degrees (63.11%), visiting cafés several times a month (47.09%), and earning between IDR 2,000,000 - IDR 5,000,000 monthly (54.36%)

Table 1. Demographic Profile

Demografic Profile	Category	Amount	Percentage
Gender	Male	104	50.49%
	Female	102	49.51%
Age	18 - 19	44	21.36%
	20 - 21	98	47.57%
	22 - 23	50	24.27%
	24 - 25	4	1.94%
	26 - 27	4	1.94%
	28 - 29	5	2.43%
	30 - 31	0	0%
	32 - 33	1	0.49%
Domicile	Jakarta	76	36.98%
	Bogor	33	16.02%
	Depok	24	11.65%
	Tangerang	39	18.93%
	Bekasi	23	11.17%
	Outside of greater Jakarta who have used QR code menus in cafés in greater Jakarta	11	5.34%
Occupation	Employee	6	2.91%
	Self-employed	12	5.83%
	Student	188	91.26%
Education Level	Diploma Degree	4	1.94%
	Bachelor Degree	130	63.11%
	High School	72	34.95%
Frequency of Café Visits	Rarely (less than 4 times)	51	24.76%
	Several times (3<n<10 times)	97	47.09%
	Frequently (more than 9 times)	58	28.16%
Monthly Income	< IDR 2,000,000	69	33.50%
	IDR 2,000,000 - IDR 5,000,000	112	54.36%
	IDR 5,000,001 - IDR 8,000,000	14	6.80%
	IDR 8,000,001 - IDR 12,000,000	4	1.94%
	> IDR 12,000,000	7	3.40%

Source: Processed Data, 2025

The outer model test assesses a research model's validity and reliability by examining the relationship between latent variables and their indicators. Key parameters evaluated include Indicator Reliability, Internal Consistency Reliability, Convergent Validity, and Discriminant Validity. Based on Table 2, all items are already more than 0.7. A couple of items (i.e., EV1 and BI2) are removed to meet the validity and reliability criteria.

Table 2. Indicator Reliability

Variable	Item	Outer Loadings
Performance Expectancy	PE1	0.925
	PE2	0.924
	PE3	0.927
Effort Expectancy	EE1	0.844
	EE2	0.821
	EE3	0.845
Social Influence	SI1	0.919
	SI2	0.905
	SI3	0.894
Facilitating Condition	FC1	0.844
	FC2	0.899
	FC3	0.841
Habit	HT1	0.930
	HT2	0.899
	HT3	0.868
Epistemic Value	EV2	0.938
	EV3	0.929
Behavioral Intention	BI1	0.867
	BI3	0.917
	BI4	0.881
Use Behavior	UB1	0.829
	UB2	0.872
	UB3	0.850

Source: Processed Data, 2025

Table 3. Internal Consistency Reliability

Variable	Cronbach's alpha	Composite reliability (rho_a)
Performance Expectancy	0.916	0.920
Effort Expectancy	0.781	0.783
Social Influence	0.891	0.893
Facilitating Condition	0.828	0.850
Habit	0.881	0.882
Epistemic Value	0.852	0.855
Behavioral Intention	0.867	0.869
Use Behavior	0.809	0.813

Source: Processed Data, 2025

Based on the table's data, all variables in this study exhibit good internal reliability. According to Hair, Hult, Ringle, & Sarstedt (2022) the Composite reliability (ρ_a) values for all constructs are above 7.0 and below 0.95. Furthermore, the Cronbach's alpha values for all variables are also greater than 0.70, which is the standard threshold for reliability. Thus, it can be concluded that the data used to measure each construct has adequate internal consistency and is considered reliable.

Table 4. Convergent Validity

Variable	Average Variance Extracted (AVE)	Description
Performance Expectancy	0.856	Valid
Effort Expectancy	0.695	Valid
Social Influence	0.821	Valid
Facilitating Condition	0.742	Valid
Habit	0.809	Valid
Epistemic Value	0.871	Valid
Behavioral Intention	0.790	Valid
Use Behavior	0.723	Valid

Source: Processed Data, 2025

Based on the table and the criteria from Hair et al. (2022), all variables in this study exhibit good convergent validity. The Average Variance Extracted (AVE) value for each variable is above the recommended threshold of 0.50, which means that each construct, on average, explains more than half of the variance of its indicators. For example, Performance Expectancy has an AVE of 0.856 and Epistemic Value has an AVE of 0.871, indicating that these constructs are highly effective in explaining the variance of their measurement items. Therefore, it can be concluded that all measurement items strongly reflect their respective latent constructs.

Discriminant Validity

To measure the extent to which a construction is empirically different from other constructs in a structural model, discriminant validity is carried out. In this study, discriminant validity was measured based on three stages of testing, namely Cross Loadings, Fornell-Larcker, and Heterotrait-Monotrait Ratio (HTMT) (Hair et al., 2022).

Table 5. Cross Loadings

	PE	EE	SI	FC	HT	EV	BI	UB
PE1	**0.925**	0.677	0.558	0.298	0.603	0.559	0.578	0.630
PE2	**0.924**	0.655	0.557	0.285	0.560	0.575	0.583	0.593
PE3	**0.927**	0.646	0.570	0.400	0.593	0.624	0.652	0.598
EE1	0.626	**0.844**	0.457	0.220	0.573	0.500	0.572	0.592
EE2	0.541	**0.821**	0.551	0.312	0.533	0.490	0.529	0.574
EE3	0.608	**0.835**	0.563	0.391	0.513	0.580	0.602	0.538
SI1	0.567	0.587	**0.919**	0.372	0.650	0.644	0.659	0.653
SI2	0.537	0.592	**0.905**	0.344	0.578	0.599	0.624	0.644
SI3	0.546	0.532	**0.894**	0.471	0.583	0.692	0.696	0.623
FC1	0.270	0.293	0.315	**0.844**	0.460	0.571	0.467	0.349
FC2	0.363	0.389	0.460	**0.899**	0.577	0.688	0.621	0.489
FC3	0.276	0.259	0.340	**0.841**	0.463	0.590	0.488	0.363
HT1	0.542	0.561	0.580	0.592	**0.930**	0.712	0.737	0.707
HT2	0.545	0.537	0.593	0.522	**0.899**	0.678	0.711	0.709
HT3	0.619	0.648	0.625	0.468	**0.868**	0.689	0.723	0.696
EV2	0.615	0.609	0.668	0.680	0.730	**0.938**	0.794	0.670
EV3	0.569	0.566	0.665	0.666	0.709	**0.929**	0.740	0.648
BI1	0.624	0.616	0.627	0.460	0.700	0.682	**0.867**	0.734
BI3	0.608	0.640	0.698	0.554	0.764	0.757	**0.917**	0.763
BI4	0.512	0.562	0.618	0.636	0.679	0.754	**0.881**	0.688
UB1	0.593	0.620	0.553	0.406	0.653	0.581	0.642	**0.829**
UB2	0.591	0.562	0.641	0.424	0.701	0.632	0.686	**0.872**
UB3	0.497	0.559	0.605	0.378	0.645	0.588	0.755	**0.850**

Source: Processed Data, 2025

The table confirms discriminant validity, as all indicators exhibit higher loadings on their intended constructs than on any other. For instance, Performance Expectancy

(PE) indicators (PE1, PE2, PE3) load strongly on PE (0.925, 0.924, 0.927) compared to other constructs.

Table 6. Fornell-Larcker Criterion

	BI	EE	EV	FC	HT	PE	SI	UB
BI	**0.889**							
EE	0.683	**0.833**						
EV	0.823	0.630	**0.933**					
FC	0.618	0.371	0.721	**0.862**				
HT	0.805	0.647	0.771	0.587	**0.899**			
PE	0.655	0.712	0.635	0.357	0.633	**0.925**		
SI	0.730	0.628	0.714	0.440	0.666	0.607	**0.906**	
UB	0.820	0.680	0.706	0.472	0.783	0.656	0.706	**0.850**

Source: Processed Data, 2025

The Fornell-Larcker Criterion results confirm discriminant validity for all constructs, as their diagonal values (square root of AVE) are consistently higher than their correlations with other constructs.

Table 7. Heterotrait-Monotrait Ratio (HTMT)

	BI	EE	EV	FC	HT	PE	SI	UB
BI								
EE	0.827							
EV	0.956	0.769	0.818					
FC	0.720	0.451	0.451	0.851				
HT	0.920	0.781	0.781	0.889				
PE	0.732	0.840	0.840	0.716	0.704			
SI	0.827	0.755	0.755	0.817	0.752	0.671		
UB	0.975	0.860	0.860	0.850	0.928	0.766	0.831	

Source: Processed Data, 2025

According to Gaskin, Godfrey, & Vance (2018) and Henseler, Ringle, & Sarstedt (2015), HTMT should be less 1. After removing items BI2 and EV1, all HTMT values met the discriminant validity criteria.

In PLS-SEM, the structural or inner model delineates relationships between latent variables, grounded in theoretical frameworks and encompassing both exogenous and endogenous constructs. This model visually represents hypotheses, analyzes causal links, and assesses predictive capabilities. Its evaluation involves testing the Variance Inflation Factor (VIF), coefficient of determination (R^2), predictive power, and path coefficients. To assess collinearity, the Variance Inflation Factor (VIF) is used. As shown in Table 8, in this study, all VIF values were below 5, confirming non-problematic multicollinearity. According to Hair et al. (2022), VIF < 5 indicates that each exogenous construct contributes distinct information in explaining the endogenous (dependent) variable.

Table 8. Variance Inflation Factor (VIF)

	VIF
Performance Expectancy → Behavioral Intention	2.425
Effort Expectancy → Behavioral Intention	2.480
Social Influence → Behavioral Intention	2.425
Facilitating Condition → Behavioral Intention	2.254
Habit → Behavioral Intention	2.977
Epistemic Value → Behavioral Intention	4.576
Behavioral Intention → Use Behavior	1.000

Source: Processed Data, 2025

Table 9. Coefficient of Determination

	R^2	R^2 **adjusted**
Behavioral Intention	0.782	0.776
Use Behavior	0.673	0.671

Source: Processed Data, 2025

In addition, the coefficient of determination (R^2) results indicate the model's explanatory power. For Behavioral Intention, the R^2 value is 0.782, meaning 78.2% of its variance is explained by independent variables. For Use Behavior, the R^2 is 0.673, demonstrating 67.3% of its variance explained by Behavioral Intention. These findings confirm the model's robustness and effectiveness in explaining variance in both behavioral intention and use behavior.

Table 10. Predictive Power ($PLS_{predict}$)

	RMSE	
	PLS	**LM**
BI1	0.657	0.687
BI3	0.639	0.664
BI4	0.651	0.634
UB1	0.690	0.729
UB2	0.765	0.823
UB3	0.793	0.852

Source: Processed Data, 2025

The $PLS_{predict}$ test results in Table 9 confirm the PLS-SEM model's robust predictive power and accuracy as it consistently outperforms the linear model (LM) across all indicators (BI1, BI3, BI4, UB1, UB2, UB3), with lower RMSE values.

The results of hypothesis testing can be seen from Table 11.

Table 11. Path Coefficient

	Path Coefficient	T Statistics	P Values	Significant (p<0.05)
PE → BI	0.058	1.342	0.180	No
EE → BI	0.126	2.106	0.035	Yes
SI → BI	0.171	2.803	0.005	Yes
FC → BI	0.093	1.044	0.296	No
HT → BI	0.294	3.114	0.002	Yes
EV → BI	0.290	2.962	0.003	Yes
BI → UB	0.820	30.491	0.000	Yes

Source: Processed Data, 2025

The Influence of Performance Expectancy on Behavioral Intention

Performance Expectancy (PE) was hypothesized to significantly affect Behavioral Intention (BI) in QR code menu usage. However, analysis revealed a non-significant positive effect (T statistic = 1.342 < 1.96, P value = 0.180 > 0.05, Original Sample = 0.058), leading to hypothesis rejection. This contrasts with prior research by Strzelecki (2024), Ong et al. (2023), Wu & Liu (2023), and Romero-Rodríguez et al. (2023). It, however, align with prior research by Isnaini & Tulasmi (2024), suggesting that performance expectancy is less impactful in contexts involving routine tasks, where users tend to prioritize ease of use over perceived benefits. While users perceive QR code menus as beneficial and efficient, these benefits appear to be basic expectations rather than primary drivers of behavioral intention. In this study, the majority of respondents were students, a group generally characterized by higher digital literacy, familiarity with mobile technologies, and frequent exposure to online services. For these users, QR code menus are perceived as a baseline convenience that aligns with their everyday digital routines. In other words, students adopt QR code menus not because they perceive substantial performance improvements, but because the system is easy, convenient, and consistent with their digital lifestyle. Once the functional expectations of QR code menu are met, other factors like Effort Expectancy, Social Influence, Habit, or Epistemic Value may play a role in affecting behavioral intention.

The Influence of Effort Expectancy on Behavioral Intention

Effort Expectancy (EE) significantly and positively influences Behavioral Intention (BI) to use QR code menus, as evidenced by a T statistic of 2.106 (>1.96), P value of 0.035 (<0.05), and path coefficient of 0.126. This finding, consistent with UTAUT2 and prior research by Ong et al. (2023), confirms that perceived ease of use is a critical factor in technology adoption. Respondents strongly agreed that QR code menus are easy to understand, use, and enhance efficiency, fostering a strong intention to continue using them. The simplicity and user-friendly design of QR code menus reduce perceived barriers, boost user satisfaction, and encourage repeated use, underscoring EE's vital role in driving BI.

The Influence of Social Influence on Behavioral Intention

Social Influence (SI) significantly and positively affects Behavioral Intention (BI) to use QR code menus, indicated by a T-statistic of 2.803 (>1.96), p-value of 0.005 (<0.05) and path coefficient of 0.171. This supports the hypothesis that peer and significant other recommendations strongly shape technology adoption. Consistent with UTAUT2 and prior studies by Ong et al. (2023), social influence fosters a supportive environment, boosting user confidence and willingness to adopt, and ultimately promoting QR code menus as a preferred ordering method.

The Influence of Facilitating Condition on Behavioral Intention

Facilitating Condition (FC) had a positive but not significant influence on Behavioral Intention (BI) in QR code menu usage (T-statistic = 1.044; P-value = 0.296; path coefficient = 0.093). This led to the rejection of the hypothesis, aligning with prior research by Strzelecki (2024), Wu & Liu (2023), and Bile Hassan et al. (2022). The findings suggest that essential resources like smartphones and internet connectivity are already readily accessible, making them a baseline expectation rather than a primary driver for adoption. The respondents in this study were predominantly students, a group that already possesses the necessary resources and skills to use mobile-based technologies. Students are generally equipped with smartphones, reliable internet access, and sufficient digital literacy, which reduces reliance on external support or infrastructure when using QR code menus. Because they already feel confident in their ability to use the technology independently, facilitating conditions become less relevant in shaping their intention. Moreover, ordering food through QR code menus is a low-complexity and low-resource task, unlike more demanding technologies (e.g., enterprise systems). Users only need to scan a code and navigate a digital menu which requires minimal technical support. As long as basic requirements (e.g., internet connection and smartphone availability) are met, users perceive little need for additional facilitating infrastructure. As of 2023, 82.47% of Jakarta's population owned a smartphone (Badan Pusat Statistik Provinsi DKI Jakarta, 2024). This makes facilitating conditions more of a background factor than a decisive driver of behavioral intention in this context. In such cases, facilitating conditions may only become significant when studying populations with limited digital access or in more complex technological environments. Instead, factors such as Effort Expectancy, Social Influence, Habit, or Epistemic Value played a more critical role in shaping Behavioral Intention.

The Influence of Habit on Behavioral Intention

Habit (HT) significantly and positively influences Behavioral Intention (BI) to use QR code menus. The path coefficient analysis yielded a T-statistic of 3.114 (>1.96) and a P-value of 0.002 (<0.05), with a path coefficient of 0.294. This finding aligns with UTAUT2, which defines habit as automatic behavior from prior learning. This study confirmed that respondents past experiences with QR code menus foster an intention for continued use, making the process feel natural and effortless. Consistent with Strzelecki (2024), Ong et al. (2023), and Wu & Liu (2023), habit emerged as the most dominant factor, highlighting the importance of consistent, positive user experiences in driving long-term technology adoption.

The Influence of Epistemic Value on Behavioral Intention

Epistemic Value (EV) significantly and positively influences Behavioral Intention (BI) to use QR code menus, supported by a T-statistic of 2.962 (>1.96) and a P-value of 0.003 (<0.05), with an original sample of 0.290. This aligns with the Theory of Consumption Values, where EV reflects curiosity, novelty, and knowledge acquisition. The study confirms that the innovative and novel aspects of QR code menus, which spark curiosity and offer unique experiences, strongly motivate adoption intentions. This highlights the critical role of engaging and new features in driving technology acceptance (Ong et al., 2023).

The Influence of Behavioral Intention on Use Behavior

Behavioral Intention (BI) significantly and positively influences Use Behavior (UB) in the context of QR code menu usage. The path coefficient analysis yielded a T-statistic of 30.491 (>1.96) and a P-value of 0.000 (<0.05), with a path coefficient value of 0.820. This finding supports the hypothesis and aligns with the UTAUT2 framework, which posits that BI is a key determinant of actual technology use. Consistent with previous studies by Strzelecki (2024), Ong et al. (2023), and Wu & Liu (2023), a strong intention to use QR code menus translates into frequent and consistent usage.

Conclusion

This study confirms that the UTAUT2 model is applicable to the adoption of QR code menus in Greater Jakarta. It concludes that Effort Expectancy, Social Influence, Habit, and Epistemic Value all have a significant and positive influence on Behavioral Intention, which then leads to Use Behavior. Conversely, Performance Expectancy and Facilitating Condition were found to have no significant effect on Behavioral Intention. This suggests that these factors act as baseline expectations rather than primary motivators for adoption in this specific context. Habit emerged as the most impactful factor on Behavioral Intention, while a strong Behavioral Intention consistently translated into higher Use Behavior.

For practical recommendations, café owners and managers in Greater Jakarta should prioritize improving aspects of QR code menus that align with the significant factors. This includes emphasizing faster service benefits (Performance Expectancy), implementing user-friendly interfaces (Effort Expectancy), leveraging social recommendations (Social Influence), consistently encouraging customers to use QR code menus (Habit), and offering innovative features like chef videos to appeal to curiosity (Epistemic Value). While Performance Expectancy was found not statistically significant, continuously highlighting time savings and hygiene benefits will reinforce the overall positive perception of QR code menus benefits and encourage sustained adoption. In addition, ensuring accessible "QR Help" assistance and guidance from staff can be considered to maintain continuous usage.

This study has several limitations. It only focuses on Greater Jakarta areas which has relatively high technology adoption rates so that it cannot be generalized to the wider Indonesian context. Expanding the research scope to regions beyond Greater Jakarta areas with lower technology adoption rates in future studies would also provide a more comprehensive understanding of how the predictors in this study might have different impacts. Additionally, it only concentrates in QR code menus so that future studies could compare QR code menus with other technologies like mobile ordering apps and self-service kiosks to enhance generalizability of the research model. When QR menus incorporate direct payment functions, future research should integrate "Trust" into the UTAUT2 framework to address consumer concerns about data privacy and payment security. Furthermore, the respondents of this study were dominated by students and therefore the findings may not fully represent other population groups (e.g., working professionals, older adults, rural communities, or different income levels). Future studies should include more diverse respondent groups across age, occupation, and socio-economic backgrounds to increase generalizability.

Acknowledgment

I extend my sincere gratitude to the Faculty of Administrative Sciences, Universitas Brawijaya, for providing the academic foundation and resources essential for this research. My deepest appreciation also goes to my undergraduate thesis supervisor, Agung Nugroho Luthfi Imam Fahrudi, SAB., M.Bus.Sys.Pro., Ph.D., for his invaluable guidance, unwavering support, and insightful feedback throughout this journey.

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