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Analyzing User Continuance Intention and Continuance Behavior of Wondr by BNI with Utaut2 Model

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Abstract

Digital transformation in the banking industry prompted BNI to launch Wondr by BNI in July 2024 as a replacement for its previous mobile banking application. Despite its advanced features, the application faces significant challenges in user adoption and user complaints regarding stability and functionality. This study aims to analyze the factors influencing continuance intention and continuance behavior of Wondr by BNI users, utilizing the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. A quantitative approach was employed through an online survey of 379 Wondr users. The data were analyzed using multiple linear regression and the PROCESS macro. The results show that Performance Expectancy, Social Influence, Price Value, and Habit have a positive and significant influence on Continuance Usage Intention (CUI). In turn, Continuance Usage Behavior (CUB) is significantly influenced by Continuance Usage Intention (CUI), Facilitating Conditions (FC), and Habit (HT). Age was also found to moderate the relationship between Hedonic Motivation and CUI. These findings provide managerial implications for BNI to encourage users to download and continue using the app, which prioritizes application stability, implements age-segmented strategies, increases rewards and promotions, adds Quick Actions and Do Again features on the home screen, introduces Group features, incorporates gamification and marketing segmentation features for younger users, adds clear micro-guidance, and provides live customer service chat.

INTRODUCTION

Prior to the widespread adoption of digital technologies, the banking industry relied heavily on physical branch networks for service delivery (Arthur & Omari, 2023; Baldassarre et al., 2024; Kumari & Devi, 2022; Nguyen & Mogaji, 2022; Samuel-Ogbu, 2022; van Zanden, 2023). Customers were generally required to visit these branches to conduct essential transactions, such as withdrawing cash and checking account balances (Beju & Făt, 2023; Irfan et al., 2024; Ueda, 2024). Unlike modern systems that allow users to conduct financial transactions 24/7 without ever stepping foot inside a physical branch, this traditional model depended entirely on in-person interactions and could not offer the flexibility of remote access (Ranjan 2024).

The emergence of digital technologies in the late 20th century marked the beginning of a paradigm shift in financial service delivery. Banks began incorporating electronic systems, such as Automated Teller Machines (ATMs), online banking portals, and eventually mobile applications, to streamline operations and enhance customer convenience. The evolution of mobile banking enabled customers to perform financial transactions anytime and anywhere using smartphones and internet connectivity, significantly reducing the need for physical visits to bank branches (Ungratwar et al. 2025). This transition not only improved operational efficiency for banks but also aligned with changing consumer expectations. Looking ahead,

forecasts suggest that by 2026, 39% of Indonesian adults will have a digital bank account, reflecting the country's accelerating digital transformation in the financial sector (Statista 2023).

The urgency of this study is also in line with the increasing use of digital services in Indonesia. According to the IDN Research Institute (2025), digital finance tools have become an essential part of daily financial management for Indonesian Millennials and Gen Z, as four out of five Gen Z respondents now use digital finance apps daily. This highlights a generational shift toward tech-integrated financial management. Data reveals that 60% of young people choose mobile banking and 58% use e-wallets, thus underlining a strong inclination toward mobile-based and contactless transactions over conventional banking systems. These numbers clearly demonstrate how Millennials and Gen Z are not only adopting digital tools but also reshaping the landscape of financial services in Indonesia. However, the increase in users does not necessarily guarantee long-term loyalty, especially if the platform fails to build trust or is unable to respond to user expectations in a sustainable manner. Therefore, this study focuses on Millennial and Gen Z users as the population to be tested, considering that these generations represent the largest adopters of digital financial services and their perceptions will be critical in determining the long-term success of platforms such as Wondr by BNI.

Indonesia's banking sector is dominated by key players such as Bank Rakyat Indonesia (BRI), Bank Central Asia (BCA), Bank Mandiri, and Bank Negara Indonesia (BNI). These banks have introduced super-apps to streamline banking and financial services into a single platform, such as Livin' by Bank Mandiri, BRImo by Bank BRI, myBCA by Bank BCA, and Wondr by BNI. Primarily, this research focuses on the BNI mobile banking application.

Over the past decade, the competitive landscape among Indonesia's top banks has remained intense. In 2021, market dominance was characterized by asset value, with Bank Mandiri holding the largest share at Rp1,584.1 trillion, followed by BRI with Rp1,411.05 trillion, and BCA with assets exceeding one trillion rupiah (Luthfa 2024). This competitiveness has continued and evolved into 2024, now characterized by a race for customer base expansion and digital adoption among BRI, BNI, BCA, and Mandiri (Putri 2024). These banks have engaged in significant digital transformation efforts to stay competitive in an era where customer preferences increasingly favor mobile banking. This demonstrates the growing reliance on banking services among Indonesians and highlights the need for continuous innovation in financial technology.

BNI's transformation journey reflects the evolution of Indonesia's banking industry from traditional branch-based services to modern digital banking. Established in 1946 as the first state-owned bank in independent Indonesia, BNI initially relied entirely on in-branch teller services while rapidly expanding its domestic and international presence, including opening its first overseas branch in Singapore in 1955. Major technological advancement began in the early 1990s when BNI became one of the first banks in Indonesia to introduce Automated Teller Machines (ATMs), providing customers with greater flexibility to conduct transactions without visiting branches and marking a significant milestone in the modernization of national banking services.

Following the success of ATMs, BNI continued strengthening its digital service ecosystem throughout the 1990s and 2000s by expanding its ATM network and joining major interbank ATM networks such as ATM Bersama, PRIMA, and Link. Parallel to this development, BNI introduced 24-hour phone banking services and later SMS banking, enabling customers to perform basic financial transactions remotely through mobile phones even without internet access. These initiatives demonstrated BNI's strong adaptability to technological change and helped gradually transition customer behavior from physical to digital service channels.

BNI's digital transformation further accelerated with the launch of Internet Banking in

2007 and the subsequent development of mobile banking applications. Internet Banking allowed customers to conduct comprehensive banking activities online, while the later introduction of BNI Mobile Banking and eventually Wondr by BNI represented a shift toward more advanced, lifestyle-integrated digital platforms. With enhanced features such as financial insights, goal-based savings, investment access, and improved user experience, BNI strengthened its position in Indonesia's digital banking landscape. The evolution from teller services to ATMs, phone and SMS banking, internet banking, and full-featured mobile applications reflects BNI's continuous commitment to innovation and customer-centric digital transformation.

This study is grounded in the original UTAUT2 framework developed by Venkatesh et al. (2012). This study analyzes seven independent variables (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit), two dependent variables (continuance intention and continuance behavior), and three moderating variables (age, gender, and experience). While UTAUT2 was initially designed to explain general consumer technology adoption, this research applies the model specifically in a post-adoption context to explore the factors influencing users' continued engagement with Wondr by BNI.

Performance expectancy is defined as the degree to which a user believes that using a particular technology will help them achieve better task performance (Venkatesh et al. 2012). In the context of this study, performance expectancy refers to the belief that using Wondr by BNI enables users to manage their finances more effectively, save time, and complete banking tasks with greater efficiency.

This construct has been consistently identified as a critical determinant in technology adoption and post-adoption contexts. For example, Kilani et al. (2023) demonstrated that performance expectancy significantly influenced continuance intention in the use of e-wallet applications. Similarly, Alalwan et al. (2017) found that performance expectancy played a major role in shaping the behavioral intention of mobile banking users in Jordan. In addition, Hossain and Quaddus (2021), who integrated the ECM and UTAUT models in a post-adoption setting, confirmed that performance expectancy had a significant positive effect on users' intention to continue using mobile payment services.

This study adopts the UTAUT2 framework to examine factors influencing continuance intention (CUI) and continuance behavior (CUB) of Wondr by BNI. Performance expectancy and effort expectancy are expected to enhance continuance intention by providing perceived benefits and ease of use. Social influence is assumed to reinforce sustained usage through peer norms, while facilitating conditions support both intention and actual usage by ensuring adequate resources and support. Hedonic motivation and price value are also expected to positively influence continuance intention by increasing user satisfaction and perceived value. Habit plays a key role in strengthening both continuance intention and usage behavior through repeated use. Furthermore, continuance intention is expected to directly influence continuance behavior. Finally, age is considered a moderating variable that may affect the strength of these relationships across different user groups.

The study is grounded in a modified UTAUT2 model to examine the moderating effect of age on the relationship between various predictors, including habit, hedonic motivation, and facilitating conditions, and continuance intention. The model illustrates the conceptual importance of age as a moderating variable in CUI contexts. Therefore, the proposed hypothesis:

H11. Age moderates the relationship between Habit (HT) and Continuance Usage Behavior (CUB).

H12. Age moderates the relationship between Habit (HT) and Continuance Usage Intention (CUI).

H13. Age moderates the relationship between Price Value (PV) and Continuance Usage Intention (CUI).
H14. Age moderates the relationship between Hedonic Motivation (HM) and Continuance Usage Intention (CUI).
H15. Age moderates the relationship between Facilitating Conditions (FC) and Continuance Usage Intention (CUI).

RESEARCH METHOD

To ensure accurate and culturally relevant interpretation, the questionnaire was initially prepared in English and then translated into Bahasa Indonesia using the back-translation method. This step was taken to minimize misinterpretation due to semantic or cultural differences, considering that Bahasa Indonesia is the first language of most respondents. The research variables were assessed using a Likert scale. According to Joshi et al. (2015), the Likert scale allows researchers to structure and quantify subjective responses related to social phenomena. In this study, the questionnaire was developed using a 4-point Likert scale, ranging from 1 = Strongly Disagree to 4 = Strongly Agree, to measure respondents' levels of agreement with each statement related to the research variables. Adelson and McCoach (2010) highlighted how the design of response scales influences student attitudes. Their findings show that using a four-point Likert scale, which removes the neutral midpoint, leads students to make more definitive choices compared to a five-point scale. This suggests that the absence of a neutral option may reduce ambiguity in responses and enhance data clarity. This type of scaling allowed for the quantification of subjective data and enabled further statistical analysis.

The type of data used in this study was quantitative data, obtained by distributing questionnaires to respondents. Quantitative data were used to measure the relationships between independent variables, moderating variables, and the dependent variable in the UTAUT2 model. The data source in this study consisted of primary data obtained directly from respondents through an online questionnaire. This research was conducted online across all regions of Indonesia. The data collection process was carried out from July to August 2025, covering the stages of questionnaire design, pre-testing, distribution, data collection, and initial data analysis.

In this study, data collection used a survey method, with an online questionnaire administered via Google Forms. This approach was chosen to efficiently reach a wide range of respondents who were active users of the Wondr by BNI application. The questionnaire was distributed via social media platforms as well as other digital channels to ensure broader accessibility and coverage. The sampling method applied was convenience sampling, a form of non-probability sampling that selects respondents based on criteria relevant to the study objectives.

The study targeted individuals aged 17 years and above, as this represents the minimum legal age for independently opening a mobile banking account under one's own name. This demographic was highly relevant, as younger users are generally more familiar with digital technologies and tend to prefer mobile-based financial solutions such as Wondr by BNI. The focus on younger, tech-savvy users is supported by prior research. For example, Kilani et al. (2023) found that over 90% of e-wallet users were between the ages of 18 and 35, indicating that post-adoption behavior is especially relevant within this age range. Similarly, Putri et al. (2022) identified that young users were significantly influenced by performance expectancy, hedonic motivation, and habit when using mobile banking applications. The target population in this study covered users who owned a personal Wondr by BNI account (independent from parental monitoring) and who had used the application at least once in the past month, ensuring that their responses reflected recent experiences.

The population (N) for this study was the total number of Wondr by BNI users as of

March 2025, which was 6,800,000 users. To determine the minimum required sample size (n) from this known population, Slovin's formula was used. This calculation was made using a 95% confidence level, which corresponds to a 6% margin of error (e = 0.06), an acceptable standard in social science research. As stated by Iba and Wardhana (2024), Slovin's formula is one option for determining sample size when the population size is known. Based on the calculation, the minimum required sample size for this study was 278 respondents. This study successfully collected data from 379 respondents; therefore, this number comfortably exceeded the minimum requirement.

RESULTS AND DISCUSSION

Multiple Linear Regression Testing

1) The Baseline Model to CUI (Phase 1)

The first multiple regression analysis was used in this study to systematically identify relationship patterns in direct effect variable such as the relationship between the independent variables of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit and the dependent variable of Continuance Usage Intention. The statistical results obtained from the multiple linear regression analysis are presented in Table 1 and 2.

Table 1. Result of multiple linear regression test

Model	R Square	Adjusted R^2	Std. Error	F test	Sig.	Category
1 (DV = CUI)	0.650	0.643	0.93038	98.439	0.000	Suitable model

Source: Primary data processed by the author using SPSS, 2025

Table 2. Result of multiple linear regression test path to CUI

Path of Influence to CUI	B (Unstd.)	*t*	Sig.	Hypothesis Result
(Constant)	.520	1.292	.197	Insignificant
PE -> CUI	**.119**	**2.986**	**.003**	**H1 Accepted**
EE -> CUI	.061	1.496	.135	H2 Rejected
SI -> CUI	**.124**	**3.149**	**.002**	**H3 Accepted**
FC -> CUI	-.046	-1.137	.256	H4 Rejected
HM -> CUI	.054	1.886	.060	H5 Rejected
PV -> CUI	**.379**	**6.605**	**.000**	**H6 Accepted**
HT -> CUI	**.169**	**4.622**	**.000**	**H7 Accepted**

Source: Primary data processed by the author using SPSS, 2025

Dependent: Continuance Usage Intention (Y1)

According to the findings from table 4, Performance Expectancy (PE), Social Influence (SI), Price Value (PV), and Habit (HT) were the factors found to have positive and significant influences on the Continuance Usage Intention of Wondr by BNI. These findings supported hypotheses H1, H3, H6, and H7. Meanwhile, EE, FC, HM was found insignificant.

2) The Baseline Model to CUB (Phase 2)

The second multiple regression analysis was used in this study to systematically identify relationship patterns in direct effect variable such as the relationship between the independent variables of Facilitating Conditions, Habit and the dependent variable of Continuance Usage Behavior. The statistical results obtained from the multiple linear regression analysis are presented in Table 3 and 4.

Table 3. Result of multiple linear regression test

Model	R Square	Adjusted R^2	Std. Error	F test	Sig.	Category
2 (DV = CUB)	0.630	0.627	0.91673	212.514	0.000	Suitable model

Source: Primary data processed by the author using SPSS, 2025

Table 4. Result of multiple linear regression test path to CUB

Path of Influence to CUB	B (Unstd.)	t	Sig.	Hypothesis Result
(Constant)	1.070	2.851	.005	Significant
CUI -> CUB	**.355**	**8.050**	**.000**	**H8 Accepted**
FC -> CUB	**.194**	**5.703**	**.000**	**H9 Accepted**
HT -> CUB	**.215**	**6.475**	**.000**	**H10 Accepted**

Source: Primary data processed by the author using SPSS, 2025

Dependent: Continuance Usage Behavior (Y2)

The results of further analysis of CUB are set out in Table 4. It revealed the significant influences of all three direct variables tested (Continuance Usage Intention (CUI), Facilitating Conditions (FC), and Habit (HT)) on the Continuance Usage Behavior using Wondr by BNI. The outputs strongly supported hypotheses H8, H9, and H10.

3) Confirmatory Moderation Analysis

After estimating the baseline multiple-linear-regression model, moderator variables were examined separately using PROCESS (Model 1). Moderation analysis was conducted to test whether the effects of the independent variables (HT, PV, HM, FC) on the outcomes (CUI, CUB) were dependent on age, gender, or experience. A moderation effect is confirmed by a statistically significant interaction term between an independent variable and a moderator.

A mediation analysis in Table 5 and 6 was conducted using the PROCESS macro for SPSS (Model 4) developed by Andrew Hayes. This method was chosen for its robustness in estimating both direct and indirect effects. The "Effect" was used to determine the magnitude and direction of the relationships between variables.

For direct effects, statistical significance was determined using the p-value, with a conventional alpha level of $p < .05$. For indirect effects, significance was determined using bootstrapping with 5,000 samples. This technique is superior to older methods (like the Sobel test) because it does not assume a normal distribution for the indirect effect, which is often skewed. Bootstrapping generates a 95% confidence interval (CI), represented by a lower limit (BootLLCI) and an upper limit (BootULCI). If the interval between the LLCI and ULCI does not contain zero, the indirect effect is considered statistically significant. This method provides a more accurate and reliable test of mediation.

The mediation analysis was conducted to test the hypothesis that demographic variables (age, gender, and experience) would mediate the relationships between the UTAUT2 predictors and the outcome variables. The results, however, do not support this objective.

The analysis revealed that for 14 out of the 15 tested paths, the indirect effect was not significant, as indicated by the 95% bootstrapped confidence intervals containing zero. This demonstrates a consistent pattern of no mediation for nearly all tested relationships.

A single exception was found for the path Hedonic Motivation → Age → Continuance Usage Intention, where a statistically significant partial mediation was detected (Indirect Effect = -.0191, 95% BCI [-.0394, -.0034]). In non-statistical terms, this "partial" mediation implies a dual pathway, like having both a main road and a bridge to reach a destination. The direct influence of Hedonic Motivation on Intention (the main road) remains active and significant. However, the "bridge" path is also active. In this case, Age acts as the bridge, carrying some

of the influence. This "partial" mediation means that the direct relationship (the main road) would still exist and function even without this bridge.

Table 5. Result of indirect mediator in Hayes PROCESS macro

Path of Influence	Indirect Effect				Output	Conclusion
	Coeff.	Effect	Boot LLCI	Boot ULCI		
HT -> Age -> CUI	.0057	.0018	-.0071	.0109	Not Sig	No Mediation
PV -> Age -> CUI	.0176	.0061	-.0030	.0184	Not Sig	No Mediation
HM -> Age -> CUI	**.0765**	**-.0191**	**-.0394**	**-.0034**	**Sig**	**Partial Mediation**
FC -> Age -> CUI	.0428	.0051	-.0033	.0161	Not Sig	No Mediation
HT -> Gender -> CUI	-.1289	.0056	-.0035	.0169	Not Sig	No Mediation
PV -> Gender -> CUI	-.0921	.0062	-.0075	.0223	Not Sig	No Mediation
HM -> Gender -> CUI	-.5345	.0040	-.0097	.0185	Not Sig	No Mediation
FC -> Gender -> CUI	-.4677	.0072	-.0047	.0205	Not Sig	No Mediation
HT -> Experience ->CUI	.0003	-.0001	-.0074	.0080	Not Sig	No Mediation
HM -> Experience -> CUI	-.0467	-.0023	-.0117	.0075	Not Sig	No Mediation
FC -> Experience -> CUI	-.0375	.0010	-.0067	.0109	Not Sig	No Mediation
HT -> Age -> CUB	.0134	.0043	-.0034	.0135	Not Sig	No Mediation
HT -> Gender -> CUB	-.1070	.0047	-.0044	.0145	Not Sig	No Mediation
HT -> Experience -> CUB	.0084	-.0017	-.0097	.0052	Not Sig	No Mediation
CUI -> Experience -> CUB	-.0036	.0007	-.0063	.0082	Not Sig	No Mediation

Source: Primary data processed by the author using Hayes PROCESS Macro, 2025

Table 6. Result of direct mediator in Hayes PROCESS macro

Path of Influence	Direct Effect			Output
	Effect	*t*	*p*	
HT -> Age -> CUI	.5111	18.9362	.0000	Sig
PV -> Age -> CUI	.8041	21.1955	.0000	Sig
HM -> Age -> CUI	.3507	9.3137	.0000	**Sig**
FC -> Age -> CUI	.4864	13.4085	.0000	Sig
HT -> Gender -> CUI	.5073	18.7458	.0000	Sig
PV -> Gender -> CUI	.8040	20.9047	.0000	Sig
HM -> Gender -> CUI	.3276	8.7151	.0000	Sig
FC -> Gender -> CUI	.4843	13.4417	.0000	Sig
HT -> Experience ->CUI	.5130	19.1451	.0000	Sig
HM -> Experience -> CUI	.3339	8.7914	.0000	Sig
FC -> Experience -> CUI	.4905	13.4902	.0000	Sig
HT -> Age -> CUB	.4923	19.0577	.0000	Sig
HT -> Gender -> CUB	.4919	18.9672	.0000	Sig
HT -> Experience -> CUB	.4982	19.4171	.0000	Sig
CUI -> Experience -> CUB	.6910	19.9198	.0000	Sig

Source: Primary data processed by the author using Hayes PROCESS Macro, 2025

4) The Role of CUI (Phase 4)

The analytical strategy for this research was conducted in distinct stages to ensure clarity and methodological accuracy, testing CUI as mediator and moderator. Initially, a multiple linear regression model was tested without the inclusion of moderating variables. The previous stage was to establish a robust baseline model and identify the confirmatory variable of moderation and mediation on age, gender, and experience. The baseline model successfully accounted for 65% of the variance in CUI and 63% of the variance in CUB. It indicated a high degree of effectiveness.

Table 7. Result of CUI as mediator indirect Hayes PROCESS macro

Path of Influence	coeff	Indirect Effect			Output	Conclusion
		Effect	BootLL CI	BootUL CI		
PE -> CUI -> CUB	.5144	.2747	.2052	.3521	Sig	Partial Mediation
EE -> CUI -> CUB	.5110	.2591	.1940	.3292	Sig	Partial Mediation
SI -> CUI -> CUB	.5610	.3094	.2392	.3782	Sig	Partial Mediation
FC -> CUI -> CUB	.5120	.2516	.1888	.3198	Sig	Partial Mediation
HM-> CUI -> CUB	.6407	.2125	.1428	.2892	Sig	Partial Mediation
PV -> CUI -> CUB	.4195	.3399	.2305	.4659	Sig	Partial Mediation
HT -> CUI -> CUB	.4179	.2143	.1565	.2766	Sig	Partial Mediation

Source: Primary data processed by the author using Hayes PROCESS Macro, 2025

Table 8. Result of CUI as mediator direct Hayes PROCESS macro

Path of Influence	Direct			Output
	Effect	*t*	*p*	
PE -> CUI -> CUB	.2203	.0000	.2747	Sig
EE -> CUI -> CUB	.2488	.0000	.2591	Sig
SI -> CUI -> CUB	.1750	.0000	.3094	Sig
FC -> CUI -> CUB	.2718	.0000	.2516	Sig
HM-> CUI -> CUB	.1012	.0009	.2125	Sig
PV -> CUI -> CUB	.4001	.0000	.3399	Sig
HT -> CUI -> CUB	.2822	.0000	.2143	Sig

Source: Primary data processed by the author using Hayes PROCESS Macro, 2025

CUI as Mediator

In the original UTAUT2 framework, behavioral intention has been defined as a "distinct endogenous construct" that directly influences usage behavior with key determinants (such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit) mainly impacting behavioral intention, while certain constructs (particularly facilitating conditions and habit) have the potential to have direct effects on usage behavior (Venkatesh *et al.* 2012). Although UTAUT2 does not label behavioral intention as a mediator, its placement suggests that predictor (X) effects pass through intention before reaching usage behavior. Accordingly, the present analysis formally tests Continuance Usage Intention (CUI) as a mediator that transmits the effects of the X predictor constructs to Continuance Usage Behavior (CUB).

A formal mediation analysis was conducted using the PROCESS macro (Model 4) in Table 7 and 8 to test the hypothesis that Continuance Usage Intention (CUI) mediates the relationship between the seven significant UTAUT2 predictors and Continuance Usage

Behavior (CUB). The data in Table 7 reveal that all seven major variables have a consistent pattern of partial mediation. The contemporary guidelines for mediation analysis (Hayes 2018) underpin this finding.

The phrase "Partial Mediation" is used when two things happen. First, the Indirect Effect is statistically significant, which it is here because the 95% bootstrap confidence interval (BootLLCI/BootULCI) for each path does not include zero. Second, The Direct Effect is also statistically significant, which it is here because $p < .05$ for all pathways. Edwards and Konold (2020) emphasize that when both the direct and indirect paths are significant, the result supports partial mediation. Similarly, Pellegrini (2025) in her psychology thesis explains that a bootstrapped indirect effect reaching significance alongside a remaining significant direct effect indicates partial mediation. Both sources reinforce the definition that partial mediation requires a significant mediator effect and a still-significant direct effect.

This is a significant and solid finding. It means that Continuance Usage Intention (CUI) is a confirmed, significant mechanism or "bridge" that explains how the predictors (like PE and HT) lead to Continuance Usage Behavior (CUB). It is called "partial" simply because CUI is not the only path. The predictors are so strong that they have an effect on CUB directly, without going through the CUI bridge. This dual influence (both indirect and direct) demonstrates that the interactions are strong and complex.

CUI as Moderator

Based on Table 9, four clear moderation patterns appear. At low Intention to continue using (CUI), SI, FC, HM, and HT have a stronger effect on CUB. At high Intention to continue using (CUI), their effect is weaker. In other words, intention levels change how much these factors move behavior. When CUI is high, SI, FC, HM, and HT change behavior only a little; when CUI is low, they change behavior more. In other words, strong intention leaves less room for SI, FC, HM, or HT to add extra usage behavior, while weak intention leaves more room for them to make a difference.

For Social Influence (SI): if a person's intention to continue using (CUI) is low and close friends recommend the app and use it daily, that social push can lead to more app openings and more completed transactions. If CUI is already high, the same encouragement changes behavior only slightly, because usage is already likely.

For Facilitating Conditions (FC): if a person's intention to continue using (CUI) is low and the app works smoothly (fast login, reliable Face ID, quick top-ups), these good conditions can lead to more completed transactions. If CUI is already high, the same smooth conditions change behavior only a little.

For Hedonic Motivation (HM): if a person's intention to continue using (CUI) is low and the app feels enjoyable (clean UI, satisfying flows, engaging rewards), that enjoyment can lift actual usage. If CUI is already high, the same enjoyable feel changes behavior only slightly.

For Habit (HT): if a person's intention to continue using (CUI) is low and a small routine is formed (e.g., paying bills every Friday via the app), that habit can give a clear boost to usage. If CUI is already high, adding more routine has only a small extra effect.

The takeaway is that these variables (SI, FC, HM, HT) interaction is negative, meaning the positive influence of factors like Social Influence on Behavior is weakened by high Intention. This pattern is supported by the negative and significant interaction terms, SI × CUI ($B = -0.044$, $p = .0007$), FC × CUI ($B = -0.038$, $p = .0017$), HM × CUI ($B = -0.047$, $p = .0008$), and HT × CUI ($B = -0.032$, $p = .0019$) showing that predictor to CUB slopes are larger at low CUI and smaller at high CUI.

Table 9. Result of CUI as moderator Hayes PROCESS macro

Path of Influence	coeff	*t*	*p*	Output	Conclusion
PE x CUI -> CUB	-.0191	-1.6942	.0911	Not Sig	No moderator
EE x CUI -> CUB	-.0185	-1.5984	.1108	Not Sig	No moderator
SI x CUI -> CUB	**-.0441**	**-3.4088**	**.0007**	**Sig**	**Moderator**
FC x CUI -> CUB	**-.0379**	**-3.1693**	**.0017**	**Sig**	**Moderator**
HM x CUI -> CUB	**-.0471**	**-3.3741**	**.0008**	**Sig**	**Moderator**
PV x CUI -> CUB	-.0238	-1.6494	.0999	Not Sig	No moderator
HT x CUI -> CUB	**-.0322**	**-3.1209**	**.0019**	**Sig**	**Moderator**

Source: Primary data processed by the author using Hayes PROCESS Macro, 2025

Final Model Result

This section presents the final outcomes of the prior phases of the empirical testing. The original research framework, shown in Fig 2, was based on the UTAUT2 model and provided a wide range of interactions. The biggest predictor of Continuance Usage Intention (CUI) was Price Value (PV) (*B*=.379), followed by Habit (HT) (*B*=.169), Social Influence (SI) (*B*=.124), and Performance Expectancy (PE) (*B*=.119), according to the hypotheses. Regarding the paths to Continuance Usage Behavior (CUB), Continuance Usage Intention (CUI) itself have the largest impact (*B*=.355), followed by Habit (HT) (*B*=.215) and Facilitating Conditions (FC) (*B*=.194). Furthermore, the framework proposed a specific moderating effect, hypothesizing that Age would significantly moderate the relationship between Hedonic Motivation (HM) and CUI.

Past the initial framework of hypotheses, more exploratory analyses showed several non-hypothesized but statistically significant relationships. These findings added a new understanding of how Wondr by BNI users continue to use the service. These findings are shown in Fig 3.

Testing Continuance Usage Intention (CUI) as a moderating variable led to a significant set of new findings. The analysis revealed that CUI significantly moderates several key relationships with Continuance Usage Behavior (CUB). Specifically, the effects of Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), and Habit (HT) on CUB were all found to be significantly influenced by the level of CUI.

Furthermore, the study identified an additional mediating role for Age. Age was found to have significant impact but only for the relationship between Hedonic Motivation (HM) and Continuance Usage Intention (CUI).

Finally, analysis formally identified Continuance Usage Intention (CUI) as a significant mediator in the relationship between all the predictors (X) and Continuance Usage Behavior (CUB).

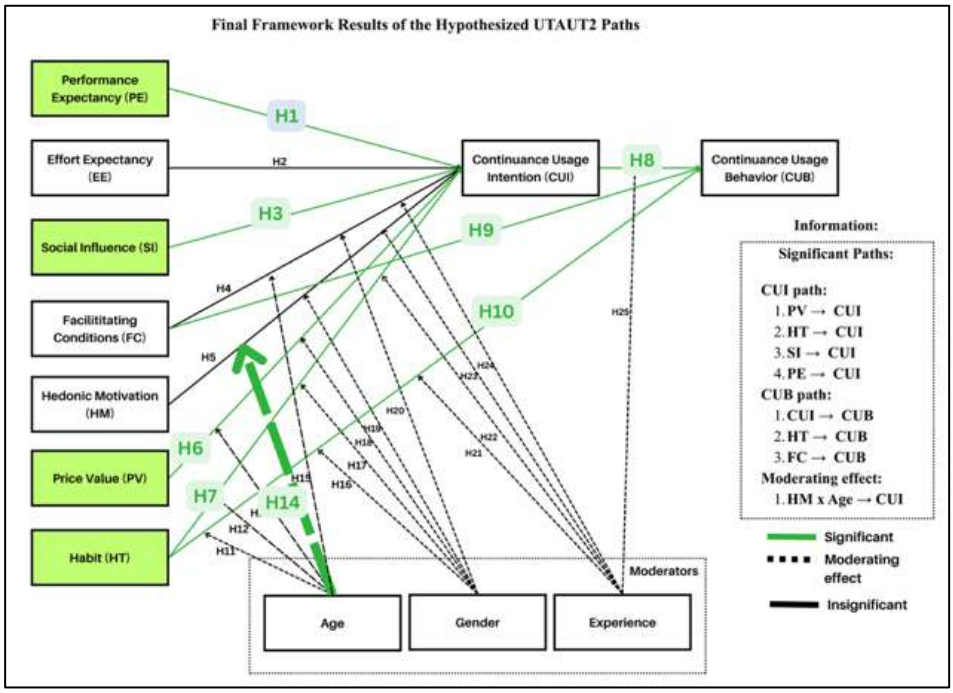

Figure 1. Final framework results of the hypothesized UTAUT2 Paths
Source: Adapted from Venkatesh et al. (2012) and developed by the author, 2025

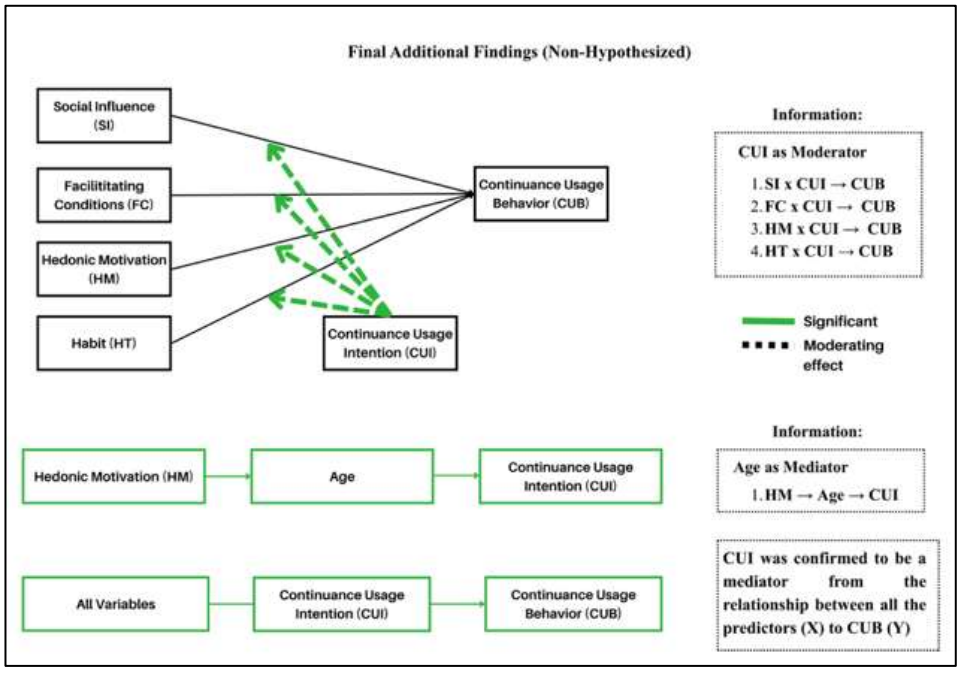

Figure 2. Final additional findings (non-hypothesized)
Source: Developed by the author based on research results, 2025

CONCLUSION

This study empirically validates the extended UTAUT2 model in predicting Wondr by BNI's post-adoption usage. Continuance Usage Intention is primarily driven by Price Value, Habit, Social Influence, and Performance Expectancy, while actual behavior is dictated by Intention, Habit, and Facilitating Conditions. Based on these findings and qualitative user feedback, several integrated managerial implications are recommended for BNI. Foremost, to address Performance Expectancy, ensuring system stability by resolving critical application

errors and transaction failures is paramount. BNI should also upgrade basic features into proactive tools, such as an "Insights and Reminder" function that anticipates upcoming bills and enables one-tap execution. To leverage Social Influence, BNI should develop a "Group" feature allowing users to save group account numbers and coordinate routine transfers effortlessly. Regarding Price Value, which is the strongest predictor of intention, BNI must optimize the cost-benefit ratio by re-evaluating transaction fees or significantly increasing tangible rewards and promotions. To solidify Habit and ensure Intention translates to behavior, the application should feature "Quick Actions" like templates and one-tap repeat transactions on the home interface, alongside contextual "micro-guidance" during moments of user hesitation to prevent task abandonment. Furthermore, enhancing Facilitating Conditions requires an accessible support infrastructure; integrating a live chat feature on error screens and deploying a real-time "System Status" page will mitigate technical failures that directly impede actual behavior. Finally, Hedonic Motivation strategies, such as gamification, must be strategically segmented. BNI should refine features like the "BNI POIN+" system to retain existing younger cohorts, who are primarily driven by hedonic motivation, rather than utilizing entertainment as an acquisition tool for older or hesitant users. For future research, it is suggested that studies incorporate longitudinal designs to examine changes in continuance behavior over time and explore additional psychological or trust-based constructs (such as perceived risk, satisfaction, or system reliability) as potential extensions of the UTAUT2 model to further improve predictive accuracy in digital banking contexts.

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