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Investigating Demographic Variations in the Use of Online Public Services: A UTAUT-Based Multigroup Analysis

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Abstract

This study aims to investigate demographic disparities in the adoption of online public services (OPS) in Vietnam, a nation experiencing rapid digital transformation while grappling with unequal access. Employing the Unified Theory of Acceptance and Use of Technology (UTAUT) as the analytical framework, data from 1,186 citizens were analyzed using PLS-SEM and multigroup analysis to determine whether the fundamental UTAUT relationships differ across these demographic segments. The findings indicate that women are more affected by family and community encouragement; ethnic minority users place greater reliance on performance expectancy "valuing time savings, reduced travel, and service accessibility" and rural users depend more on effort expectancy and facilitating conditions due to infrastructure constraints. These differences affirm that social and contextual factors significantly influence citizens' behavioral intentions toward OPS use. The study's novelty lies in incorporating demographic segmentation into the UTAUT framework within a developing-country context, thereby extending its theoretical applicability and providing actionable insights for an inclusive digital government. The results offer policymakers evidence-based guidance for designing targeted interventions to enhance accessibility and equity in Vietnam's digital transformation process.

Keywords:

e-Government;
UTAUT;
Demographic;
Multi-Group Analysis;
PLS-SEM; MICOM.

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1- Introduction

Despite significant progress in digital governance initiatives, the use and effectiveness of online public services (OPS) in Vietnam remain limited, according to a comprehensive review of 63 provincial e-service portals by the Institute for Policy Studies and Media Development and United Nations Development Program. The review found that none of the e-service portals fully met the established criteria for convenience, usability, and accessibility. All portals showed significant deficiencies in terms of access, provision of essential information, user guidance, provision of services throughout the life cycle, and accessibility for persons with disabilities. Remarkably, no portal scored more than 50 percent of the assessment criteria as 'good'. Even the highest-scoring portal achieved this in only four out of nine criteria, with minimal variation in scores between provinces, indicating systemic and widespread problems. Critical gaps in the protection of personal data and accessibility were identified. Sixty portals did not fulfill data protection standards, and 39 did not meet accessibility requirements for people with disabilities. In addition, most portals showed only average compatibility with computers and smartphones, even though over 90 percent of citizens access the internet mainly via smartphones, highlighting the urgent need for technical improvements. These findings underscore the need for comprehensive improvements in portal design, accessibility, data protection, and service delivery processes to promote citizen engagement and ensure equal access to digital public services for different demographic groups [1].

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This research gap is particularly striking given the persistent difficulties many Vietnamese citizens face in accessing and using OPS. As highlighted in the national review, barriers are particularly high for residents of remote and rural areas and groups with limited digital skills or resources, such as the elderly and ethnic minorities. Studies emphasize the critical role of the urban-rural divide, institutional capacity, and socio-cultural factors in adoption and outcomes, with rural and disadvantaged populations consistently experiencing greater barriers to access and use [2-4]. In addition, studies measuring citizen satisfaction with e-government services in Vietnam confirm that factors such as accessibility, trust, privacy, and familiarity significantly influence satisfaction, but demographic differences in these experiences are rarely studied in depth [5, 6].

Over the past two decades, global research on e-government adoption has significantly evolved, concentrating on how citizens perceive, accept, and engage with digital public services. The Unified Theory of Acceptance and Use of Technology (UTAUT), further developed in later works, has emerged as one of the most widely utilized frameworks for explaining behavioral intention and technology adoption [7, 8]. However, despite its extensive application, comparative and context-sensitive studies remain limited. While cross-country analyses and gender-based comparisons exist [9-11], few have systematically examined ethnicity or urban-rural differences, particularly in developing or transitional economies, where the digital divide remains significant. In Vietnam, the body of literature concerning OPS adoption is both fragmented and predominantly descriptive. Most research has concentrated on elements such as technical readiness, perceived service quality, or user satisfaction [5, 6]. While these studies provide valuable insights into the general factors driving acceptance, they often lack a robust theoretical framework like UTAUT and do not investigate how demographic factors might influence these relationships. Additionally, advanced statistical methods such as multigroup analysis (MGA) are rarely employed, which could otherwise uncover variations in behavioral mechanisms among different user groups. This absence of comparative evidence restricts policymakers' understanding of how demographic diversity affects digital participation, especially among vulnerable populations like ethnic minorities and rural residents.

In this context, it is important to understand the factors that influence the acceptance and use of e-government services by citizens. The UTAUT model provides a solid theoretical framework for analyzing technology acceptance, including in the area of e-government, while MGA has become increasingly important in various research areas as a means of systematically analyzing differences between population groups [12]. However, in the field of digital government, there remains a notable lack of comparative studies that utilize multigroup analyses to investigate these differences. While the MGA has been successfully applied in other contexts, its application in research on the digital state in Vietnam is still lacking, particularly with regard to vulnerable and disadvantaged groups, including older people, ethnic minorities, and those with low levels of education or income. This has led to a lack of differentiated insights into how different population groups experience, perceive, and use OPS. This gap is particularly problematic in the context of the Vietnamese government's ongoing administrative reform and digital transformation agenda, which explicitly aims to build a people-centered digital administration that leaves no one behind [13]. Without robust comparative data on demographic differences, there is a risk that policy measures will not be sufficiently targeted and may exacerbate, rather than improve, existing inequalities.

To address this gap, this study aims to investigate how demographic factors such as gender, ethnicity, and place of residence influence the determinants of OPS adoption and usage behavior by combining the strengths of the UTAUT model and the analytical power of the MGA. The rationale for this study is based on theoretical and practical considerations. Theoretically, it extends the application of UTAUT by incorporating a comparative, cross-group perspective, enriching our understanding of how OPS acceptance mechanisms may differ across social classes and contextual conditions. In practice, the findings have direct implications for policy and practice: the study identifies which groups face the greatest barriers and what specific factors drive or hinder their use of OPS, providing actionable insights for policymakers, system developers, and stakeholders. These insights can guide the development of more equitable, accessible, and user-centered digital government platforms and ensure that reforms meet the needs of all citizens, especially those at risk of digital exclusion.

The remainder of this paper is structured as follows. Section 2 provides a comprehensive literature review and develops the research hypotheses based on the UTAUT framework and relevant empirical studies. Section 3 presents the materials and methods, including sampling procedures, measurement constructs, and data analysis techniques. Section 4 reports the main results of the statistical analyses. Section 5 discusses the key findings in light of existing literature and contextual factors. Finally, Section 6 concludes the paper by summarizing the main implications, outlining its limitations, and suggesting directions for future research.

2- Literature Review and Hypothesis Development

Earlier studies of technology adoption, such as the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Diffusion of Innovation (DOI) theory, offered partial explanations for e-government use, focusing on perceived usefulness, behavioral control, and innovation diffusion, respectively. However, these models overlook key contextual and infrastructural determinants that are relevant to public service environments. The UTAUT integrates eight prior frameworks and identifies four core predictors (performance expectancy, effort expectancy, social influence, and facilitating conditions) providing a more comprehensive approach [7]. Its higher explanatory power and inclusion of environmental and social variables make it particularly suitable for examining citizens' technology acceptance in non-market settings. Given that e-government adoption is influenced by institutional trust and access conditions rather than hedonic or price-related factors, the original UTAUT model, rather than UTAUT2, is theoretically appropriate for this study's context.

The relationships within the UTAUT framework are influenced by the sociocultural and infrastructural contexts they inhabit. In Vietnam, the role of social norms and the persistent digital divide make these moderating factors particularly important. However, many Vietnamese studies tend to apply UTAUT broadly across the general population, often overlooking subgroup differences. This oversight limits the understanding of how demographic factors influence adoption dynamics. By adopting a multigroup perspective, researchers could gain deeper theoretical insights, allowing UTAUT to more accurately represent Vietnam's socio-digital environment.

2-1- Gender

Research examining gender differences in e-government adoption using the UTAUT framework has revealed complex and often inconsistent patterns. Some studies have demonstrated the moderating role of gender in the relationships between facilitating conditions and usage behavior, performance expectancy and behavioral intention, and social influence and behavioral intention [9, 14, 15]. For example, women have been found to rely more heavily on social encouragement and community support when adopting technologies, reflecting broader socio-cultural expectations and interpersonal orientations common to them. Men, on the other hand, often display higher self-efficacy and a stronger focus on task-related utility [7]. However, other empirical works have reported no statistically significant moderating effect of gender within the UTAUT framework [16, 17], suggesting that gendered variations might be context-specific and contingent on cultural, institutional, or infrastructural factors. These inconsistencies point to an unresolved empirical and theoretical gap regarding gender's role in technology acceptance. Addressing this gap will contribute significantly to the understanding of demographic influences in the context of the UTAUT. Accordingly, this study formulates hypotheses to test whether gender leads to differences in the key relationships of the UTAUT model.

H1a: The effect of effort expectancy (EE) on behavioral intention (BI) differs between male and female respondents.

H1b: The effect of performance expectancy (PE) on behavioral intention (BI) differs between male and female respondents.

H1c: The effect of social influence (SI) on behavioral intention (BI) differs between male and female respondents.

H1d: The effect of facilitating conditions (FC) on behavioral intention (BI) differs between male and female respondents.

H1e: The effect of facilitating conditions (FC) on usage behavior (UB) differs between male and female respondents.

H1f: The effect of behavioral intention (BI) on usage behavior (UB) differs between male and female respondents.

2-2- Ethnicity

Ethnicity has long been recognized as a relevant, but understudied, determinant of digital inclusion. Early studies on the digital divide identified ethnicity as a key structural variable influencing access to information technology and online services [18-20]. However, subsequent research has revealed more complex and sometimes contradictory patterns. In societies marked by deep ethnic divisions or unequal resource distribution, ethnicity significantly affects both access to and engagement with e-government services, reinforcing pre-existing inequalities and exclusionary dynamics [21]. Another study found that, contrary to their predictions, ethnicity had no significant predictive power once socioeconomic factors were controlled for, suggesting that its effects may be mediated by contextual conditions such as education, income, and regional infrastructure [22]. These divergent findings underscore the need to re-examine the moderating role of ethnicity within established theoretical models, such as the UTAUT, especially in multi-ethnic developing contexts such as Vietnam. Given the country's 53 ethnic minority groups, many of whom reside in geographically isolated areas with lower levels of digital literacy, ethnicity may shape how performance expectancy, effort expectancy, and facilitating conditions influence behavioral intentions toward using e-government services. Therefore, this study explicitly investigates ethnicity as a potential moderator in the UTAUT framework, leading to the following hypotheses:

H2a: The effect of effort expectancy (EE) on behavioral intention (BI) differs between ethnic majority and minority respondents.

H2b: The effect of performance expectancy (PE) on behavioral intention (BI) differs between ethnic majority and minority respondents.

H2c: The impact of social influence (SI) on behavioral intention (BI) differs between ethnic majority and minority respondents.

H2d: The effect of facilitating conditions (FC) on behavioral intention (BI) differs between ethnic majority and minority respondents.

H2e: The effect of facilitating conditions (FC) on usage behavior (UB) differs between ethnic majority and minority respondents.

H2f: The effect of behavioral intention (BI) on usage behavior (UB) differs between ethnic majority and minority respondents.

2-3- Residence

Research has consistently found a significant digital divide between urban and rural areas that influences the adoption of e-government services [23]. Rural residents often face significant infrastructural barriers, including limited broadband penetration, slower internet connectivity, and less reliable network infrastructure [24, 25]. Furthermore, users in rural areas often differ significantly from urban users in terms of key demographic factors such as income, education level, and digital literacy, all of which have a critical impact on their perception of effort expectation and performance expectation, ultimately shaping their behavioral intentions towards e-government adoption [26, 27]. Rural residents tend to find less conducive conditions, such as institutional support, technical assistance, and digital training programs, which are more common in urban environments [24, 28]. The dynamics of social influence also differ significantly between urban and rural areas; rural communities often rely more heavily on local interpersonal networks and informal communication channels than on formal government digital channels [29, 30]. Given the significant evidence of the urban-rural digital divide identified in previous research, it is crucial to systematically test how relationships within the UTAUT framework play out in different geographical contexts. By examining how effort expectancy, performance expectancy, social influence, and facilitating conditions differ between urban and rural respondents in shaping behavioral intentions and usage behavior towards e-government services, the following hypotheses are proposed:

H3a: The effect of effort expectancy (EE) on behavioral intention (BI) differs between urban and rural respondents.

H3b: The effect of performance expectancy (PE) on behavioral intention (BI) differs between urban and rural respondents.

H3c: The effect of social influence (SI) on behavioral intention (BI) differs between urban and rural respondents.

H3d: The effect of facilitating conditions (FC) on behavioral intention (BI) differs between urban and rural respondents.

H3e: The effect of facilitating conditions (FC) on usage behavior (UB) differs between urban and rural respondents.

H3f: The effect of behavioral intention (BI) on usage behavior (UB) differs between urban and rural respondents.

Based on these hypotheses, the current study uses a UTAUT model that integrates demographic factors (gender, ethnicity, and urban or rural residence). Figure 1 illustrates all hypothesized test relationships and highlights how effort expectancy (EE), performance expectancy (PE), social influence (SI) and facilitating conditions (FC) are expected to influence behavioral intentions (BI) and usage behavior (UB) differently in different demographic segments.

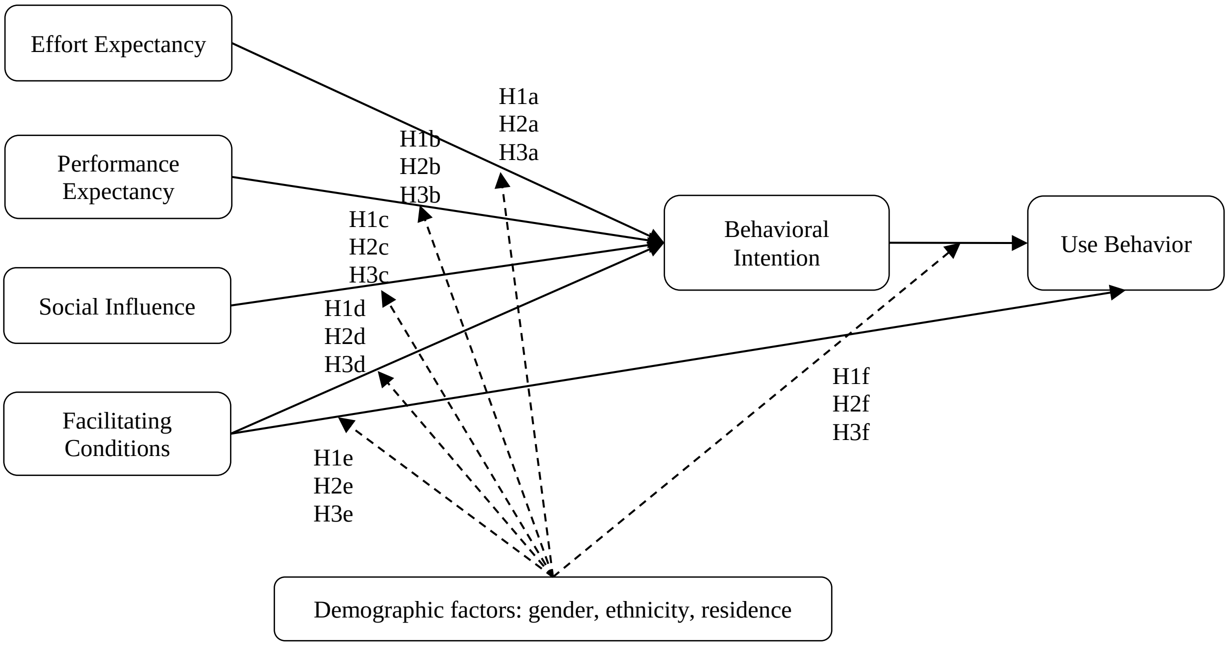

Figure 1. UTAUT model with hypothesis testing

3- Materials and Methods

3-1- Sample and Data Collection

In this study, data were collected using a structured online questionnaire created using Microsoft Forms. First, a pre-test was conducted with 150 respondents to validate the questionnaire and refine the theoretical model. Subsequently, the official survey was distributed via random email distribution targeting different demographics, including people from different universities, organizations, and regions. This broad distribution aimed to capture a representative sample across different age groups, income levels, occupations, and places of residence. To protect respondents' privacy, the questionnaire did not collect detailed personal information such as names, exact birthdays or years of birth, addresses, or exact income amounts. Instead, respondents selected the option that best represented their demographic profile using categories with specific ranges (e.g., age ranges such as 20-30, 30-40, etc.). The questions in the survey referred to the UTAUT constructs and were collected using a refined 7-point Likert scale. After three months, 1,186 valid responses were received, forming the final dataset used for the analysis. The adequacy of the sample size was confirmed using G*Power software, which resulted in a statistical power value of 1.00, which is well above the generally accepted minimum value of 0.8 for PLS–SEM studies [31, 32]. This result indicates that the achieved sample size of 1,186 respondents was sufficiently robust to reliably detect the hypothesized effects, which strengthens the credibility and generalizability of the results. Table 1 presents the demographic descriptive statistics.

Table 1. Demographic groups summary (N = 1186)

Gender	**N**	**%**
Male	468	39.5%
Female	718	60.5%
Residence	**N**	**%**
Urban	533	44.9%
Rural	653	55.1%
Ethnicity	**N**	**%**
Majority	1041	87.8%
Minority	145	12.2%
Age	**N**	**%**
20-30	415	35.0%
31-40	438	36.9%
41-50	206	17.4%
51-60	55	4.6%
>60	72	6.1%

3-2- Data Analysis

In the online survey, the data collected were thoroughly edited and cleansed to ensure accuracy, completeness, and consistency. This process included checking the dataset for missing values, incorrect entries, and possible outliers. The demographic variables were then coded into categorical areas, with gender, specific age groups, ethnicity, and place of residence clearly defined. Following data preparation, descriptive statistics were compiled using SPSS 27 software to provide a comprehensive summary of the demographic characteristics. Frequency distributions and percentages were presented for gender, age categories, ethnic groups, and place of residence, which helped create a clear demographic profile of the respondents.

The measurement model was evaluated using SmartPLS4. Confirmatory factor analysis (CFA) was performed to assess the reliability and validity of the measurement scales. Factor loadings were carefully checked to ensure that they were above the recommended threshold of 0.7. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (rho_c), with both indicators expected to exceed the guideline value of 0.7. In addition, convergent validity was confirmed by calculating the average variance extracted (AVE), with an acceptable threshold of above 0.5 [33]. Discriminant validity was tested using the Fornell-Larcker criterion and the heterotrait-to-monotrait ratio (HTMT), with HTMT values of less than 0.85 expected to ensure discriminability between constructs, or less than 0.90 for conceptually similar constructs.

Next, the structural model was evaluated. The variance inflation factor (VIF) was examined to test for multicollinearity between the predictor variables, with acceptable values of less than 5. Bootstrapping was performed in SmartPLS to validate the structural paths. The path coefficients were estimated, and their statistical significance was determined using 95% confidence intervals, t-statistics and p-values [34]. The magnitude of the effects was assessed using effect sizes (f^2) with the following cut-off values: ≥ 0.02 is small; ≥ 0.15 is medium; ≥ 0.35 is large [35]. The explanatory power of the model was indicated by R^2 and adjusted R^2 values of 0.67 (considerable), 0.33 (moderate), and 0.19 (weak) [36]. The Q^2 value is used to assess the predictive accuracy of the PLS path model. For a given endogenous construct, a Q^2 value greater than zero is necessary to confirm the structural model's predictive accuracy for that construct. Typically, Q^2 values above 0, 0.25, and 0.50 are indicative of small, medium, and large predictive relevance of the PLS-path model, respectively.

A multigroup analysis (MGA) was then conducted to test for measurement invariance across different demographic groups, specifically gender, place of residence, and ethnicity. Despite the large overall sample, unequal subgroup sizes could negatively impact statistical power and potentially underestimate the moderating effects [37, 38]. In particular, Matthews et al. [39] warned that significant differences in subgroup size "for example, if one subgroup is more than twice as large as another" could compromise the effectiveness of the permutation tests used in the MGA. To mitigate this problem, subgroup sizes should be balanced to maximize sample variance and ensure reliable statistical tests. It is suggested to either adopt Henseler's PLS-MGA approach when testing one-sided hypotheses or randomly reduce the sample of the larger group to achieve balance between subgroups [40].

Considering these recommendations, the distribution of the subgroups in this study was carefully analyzed. The categories of gender and place of residence did not show any major differences in the distribution and, therefore, did not require any adjustments. However, the ethnicity category initially showed significant discrepancies in the size of the subgroups, with 87.8% of respondents describing themselves as majority and only 12.2% as minority. Although this distribution accurately reflects Vietnam's demographic structure, such imbalances could affect the validity of MGA results. To address these concerns, a stratified random sampling procedure was implemented in SPSS to reduce the size of the majority group from 1041 to 197 cases. To ensure that the random reduction of the ethnic majority subgroup did not compromise representativeness, comparisons were conducted between the full ($n = 1041$) and reduced ($n = 197$) samples using independent-samples t-tests and Pearson's chi-square tests across demographic and key variables. All results were non-significant ($p > 0.05$), and Cohen's d values were below 0.3, indicating negligible differences between the groups. This subgroup sample was then merged with all 145 cases from the minority group to form a balanced dataset for the ethnicity-based MGA. This adjustment resulted in a new sample of 342 respondents for the ethnic subgroup analysis. The final ethnic subsample thus maintained adequate group size and comparability and followed the recommendations of Matthews et al. [39] to increase sampling variance and ensure robustness of the MGA results.

To ensure valid comparisons between the groups, the Measurement Invariance of Composite Models (MICOM) procedure was conducted according to the three-stage approach proposed [41]. This process includes: (1) configuration invariance assessment, which confirms that the measurement model and algorithm settings are equivalent across the different groups; (2) composition invariance testing, which assesses whether the composite scores in the different groups are similarly constructed using a permutation-based correlation test with criterion $c = 1$; and (3) equality testing of the composite means and variances, also via permutation tests. These steps allow the detection of partial or complete measurement invariance, which is a prerequisite for meaningful multi-group comparisons in PLS-SEM.

After assessing measurement invariance, an MGA was conducted to determine whether the structural path relationships differed significantly between the demographic subgroups. Two non-parametric approaches were used: Henseler's MGA [42], which compares bootstrap confidence intervals between groups, and the permutation test [43], which directly tests for differences in the path coefficients. In this study, a permutation test was performed with 5 000 permutations and a two-sided test approach, as recommended in the SmartPLS guidelines. The test statistics, including p-values and confidence intervals on a percentile basis, were used to assess whether the group-specific path differences were statistically significant. The results were used to evaluate specific hypotheses (H1a to H3f) and allowed a rigorous comparison of the structural relationships of the model between the subgroups of gender, place of residence, and ethnicity.

4- Results

4-1- Reliability and Measurement Validation

The reliability and validity of the measurement model were rigorously tested using established criteria (see Table 2). First, the loadings of the indicators were analyzed to determine whether they exceeded the recommended threshold of 0.70. The results showed that the loadings of all indicators were between 0.917 and 0.970, indicating excellent reliability and strong representation of the constructs. The reliability of internal consistency was assessed using Cronbach's alpha and composite reliability (rho_c). The values of Cronbach's alpha exceeded the acceptable threshold of 0.70 and ranged from 0.890 to 0.952, indicating high internal consistency within each construct. In addition, composite reliability (rho_c), which is considered a more accurate measure of internal consistency in PLS-SEM, showed robust results ranging from 0.948 to 0.969, significantly exceeding the recommended value of 0.70 [30]. The AVE values for all constructs were well above the recommended threshold of 0.50 and ranged from 0.864 to 0.913. This confirms that each construct adequately captures the variance of the associated indicators and confirms the convergent validity of the measurement model. The assessment confirmed that the measurement model met the established reliability and validity criteria, ensuring confidence in the subsequent assessment of the structural model.

Table 2. Reliability and validity assessment

Variable	Indicator	Loading	Cronbach's Alpha	Composite reliability (rho_c)	AVE
EE	EE1	0.953	0.945	0.965	0.902
	EE2	0.957			
	EE3	0.939			
PE	PE1	0.957	0.952	0.969	0.913
	PE2	0.960			
	PE3	0.949			
SI	SI1	0.946	0.890	0.948	0.901
	SI2	0.952			
FC	FC1	0.940	0.942	0.963	0.897
	FC2	0.961			
	FC3	0.939			
BI	BI1	0.934	0.950	0.969	0.911
	BI2	0.959			
	BI3	0.970			
UB	UB1	0.931	0.921	0.950	0.864
	UB2	0.940			
	UB3	0.917			

Table 3 shows the discriminant validity, which was assessed using the Fornell–Larcker criterion and the HTMT correlation ratio. Discriminant validity is confirmed when the square root of the AVE of each construct exceeds the correlations of the construct with other latent variables [44]. In this study, all constructs fulfilled these conditions. The diagonal values in the Fornell–Larcker matrix, which represent the square roots of the AVE, ranged from 0.929 (for UB) to 0.955 (for BI) and were greater than the corresponding off-diagonal correlations with other constructs. This result suggests that each construct shares more variance with its associated indicators than with any other construct in the model.

Table 3. Discriminant validity

HTMT							Fornell–Larcker criterion						
	BI	EE	FC	PE	SI	UB		BI	EE	FC	PE	SI	UB
BI							BI	0.955					
EE	0.798						EE	0.757	0.950				
FC	0.815	0.838					FC	0.773	0.791	0.947			
PE	0.851	0.826	0.830				PE	0.810	0.784	0.786	0.955		
SI	0.810	0.781	0.773	0.809			SI	0.746	0.716	0.708	0.744	0.949	
UB	0.894	0.773	0.819	0.815	0.812		UB	0.837	0.721	0.764	0.763	0.736	0.929

In addition, discriminant validity was further analyzed using the HTMT ratio (see Table 3), which is considered a more sensitive criterion for detecting problems with discriminant validity. A conservative threshold of 0.85 is recommended for conceptually distinct constructs and a more relaxed threshold of 0.90 for conceptually related constructs [45, 46]. The HTMT values for the outcome ranged from 0.773 to 0.894, with most construct pairs showing values well below the conservative threshold of 0.85. The highest HTMT value observed was 0.894 between performance expectancy (PE) and usage behavior (UB). Although this value approaches the more liberal threshold of 0.90, it is considered acceptable, given the theoretical relationship between these constructs in technology acceptance models such as UTAUT.

The explanatory power and predictive relevance of the structural model were assessed using R-squared (R^2) and Q-squared (Q^2) values for the endogenous constructs as presented in Table 4. The R^2 values for behavioral intention (BI) and usage behavior (UB) were 0.734 and 0.735, respectively. These values show that 73.4% of the variance in BI and 73.5% of the variance in UB were explained by the respective predictors. The adjusted R^2 values were virtually identical (0.733 for BI and 0.735 for UB), confirming the robustness of the model, with no evidence of overfitting. According to [35], R^2 values above 0.67 are considered substantial, which emphasizes the strong predictive power of the model. The model demonstrated not only strong explanatory power within the sample but also significant predictive relevance beyond it. With Q² predicted values of 0.729 for BI and 0.673 for UB, both surpassing the zero benchmark, the model exhibits a robust capacity to predict new data points. These findings confirm that the model is proficient in elucidating historical data and possesses considerable predictive validity for future outcomes. Figure 2 below presents the outcomes of the theoretical assessment of the UTAUT model, highlighting its explanatory strength. The data gathered from the sample substantiates the accuracy of the relationships posited within the UTAUT model.

Table 4. Model explanatory and predictive performance

	R^2	R^2 adjusted	Q^2predict
BI	0.734	0.733	0.729
UB	0.735	0.735	0.673

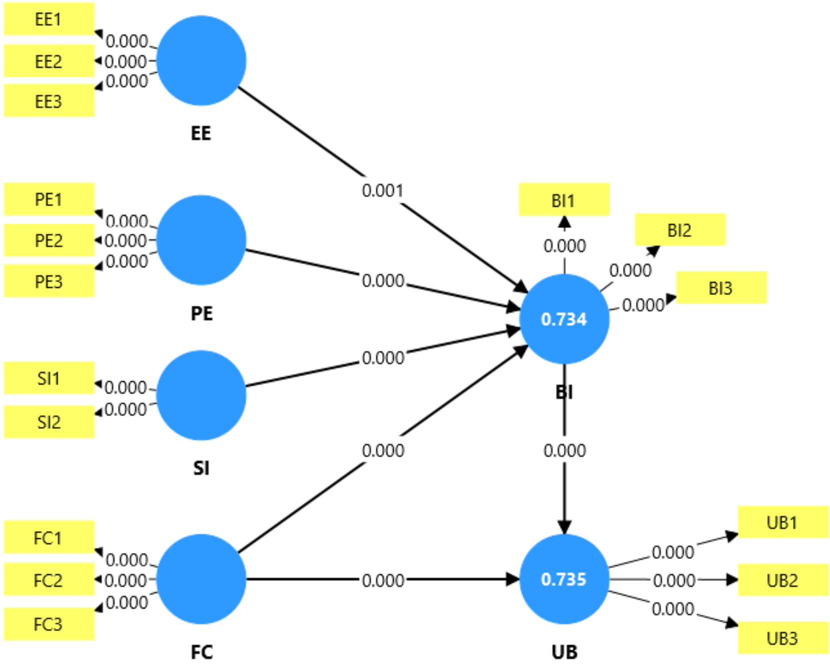

Figure 2. PLS-SEM structural model results

4-2- Structural Model Testing

The results of the structural model in Table 5 indicate that all hypothesized paths are statistically significant and have acceptable predictive relationships within the model. The VIF values for all predictors were between 2.481 and 3.593, well below the critical threshold of 5, confirming that there were no problems with multicollinearity. All path coefficients were positive and significant, with p-values below 0.05 and 95% confidence intervals that did not include zero, indicating robust support for each hypothesized relationship. In addition, the t-statistics for all paths exceeded the critical standard value of 1.96, further emphasizing their statistical significance.

In terms of effect sizes (f^2), the results ranged from small (0.022) to large (0.573), suggesting that while some predictors had modest effects (for example, EE → BI), others made a larger contribution to the variance in the dependent constructs, particularly BI → UB, which showed a strong predictive effect. Overall, these pathway results provide strong empirical support for the structural model and confirm that the proposed relationships between the constructs meaningfully explain behavioral intention and usage behavior in the studied context.

Table 5. SEM Structural path results

Path	VIF	Coefficients	95% CI	t-value	p-value	Effect size (f^2)
EE → BI	3.347	0.143	[0.069; 0.221]	3.078	0.001	0.022
PE → BI	3.593	0.363	[0.282; 0.449]	7.176	0.000	0.138
SI → BI	2.581	0.217	[0.149; 0.287]	5.179	0.000	0.069
FC → BI	3.412	0.221	[0.145; 0.301]	4.618	0.000	0.054
FC → UB	2.481	0.289	[0.229; 0.358]	7.387	0.000	0.127
BI → UB	2.481	0.614	[0.545; 0.674]	15.827	0.000	0.573

4-3- Multigroup Analysis for Different Socio-Demographic Factors

4-3-1- Gender

The results of the MICOM evaluation are shown in Table 6. In the first step, configuration invariance was determined for all six constructs, as the same measurement models and algorithm settings were used in all groups. In step 2, all constructs showed an original correlation of 1.000 with permutation values well above 0.05 (EE=0.758, PE=0.864, SI=0.265, FC=0.172, BI=0.062, UB=0.068), indicating compositional invariance. Since configural and compositional invariance were detected in both step 1 and step 2 of the MICOM procedure, partial measurement invariance was confirmed, allowing a valid comparison of path coefficients between male and female groups.

However, step 3a (equality of means) and step 3b (equality of variances) both failed, as all constructs had permutation P-values below 0.05, indicating statistically significant differences between the groups. Specifically, in Step 3a, the permutation P-values for the mean differences were as follows: EE = 0.026, PE = 0.000, SI = 0.009, FC = 0.000, BI = 0.000, and UB = 0.000. In Step 3b, the variance differences were also significant: EE = 0.000, PE = 0.000, SI = 0.000, FC = 0.001, BI = 0.000, and UB = 0.000. As a result, complete measurement invariance was not found for any construct, which means that group comparisons should be limited to structural path coefficients rather than means or variances.

Table 6. MICOM results for gender group

Constructs	Configural invariance (Same algorithms for both groups)	Compositional invariance		Partial measurement invariance established	Equal mean assessment			Equal variance assessment			Full measurement invariance established
		C=1	C.I		Diff.	C.I	Equal	Diff.	C.I	Equal	
EE	Yes	1.000	[1.000; 1.000]	Yes	-0.113	[-0.097; 0.098]	No	0.417	[-0.183; 0.178]	No	No
PE	Yes	1.000	[1.000; 1.000]	Yes	-0.209	[-0.097; 0.096]	No	0.442	[-0.208; 0.199]	No	No
SI	Yes	1.000	[1.000; 1.000]	Yes	-0.145	[-0.099; 0.099]	No	0.339	[-0.164; 0.154]	No	No
FC	Yes	1.000	[1.000; 1.000]	Yes	-0.226	[-0.097; 0.097]	No	0.443	[-0.210; 0.205]	No	No
BI	Yes	1.000	[1.000; 1.000]	Yes	-0.236	[-0.096; 0.098]	No	0.516	[-0.217; 0.204]	No	No
UB	Yes	1.000	[1.000; 1.000]	Yes	-0.215	[-0.101; 0.096]	No	0.429	[-0.209; 0.198]	No	No

The final phase of the analysis involved cross-group comparisons of pathway coefficients using Henseler's MGA and the permutation test (see Table 7). Of the six pathways analyzed, only the relationship between social influence (SI) and behavioral intention (BI) showed a statistically significant difference between men and women. Henseler's MGA was 0.012, and the permutation P-value was 0.027, which is below the recommended threshold of 0.05 and confirms a significant difference. The effect was stronger for women ($\beta = 0.287$) than for men ($\beta = 0.117$), suggesting that women are more influenced by social cues in forming their intention to use e-government services. All other paths (PE → BI, EE → BI, FC → BI, FC → UB, BI → UB) showed p-values greater than 0.05 in both the MGA and the permutation test and thus showed no statistically significant gender-specific differences. Therefore, only hypothesis 1c is supported, hypothesis 1a, 1b, 1d, 1e, and 1f are not supported.

Table 7. Multigroup analysis for gender group

Hypothesis	Path	Male	Female	Diff.	95% CI	Henseler's MGA (2-tailed)	Permutation Test (2-tailed)	Supported
H1a	EE → BI	0.179	0.118	0.061	[-0.157; 0.162]	0.269	0.264	No/No
H1b	PE → BI	0.446	0.286	0.160	[-0.171; 0.173]	0.059	0.062	No/No
H1c	SI → BI	0.117	0.287	-0.170	[-0.142; 0.140]	0.012	0.027	Yes/Yes
H1d	FC → BI	0.213	0.238	-0.025	[-0.161; 0.167]	0.388	0.394	No/No
H1e	FC → UB	0.299	0.279	0.019	[-0.133; 0.131]	0.408	0.403	No/No
H1f	BI → UB	0.635	0.591	0.044	[-0.129; 0.131]	0.278	0.294	No/No

4-3-2- Ethnicity

Similar to step 1 when analyzing the gender groups, configurational invariance was established as the same model configuration, and algorithmic specifications were used for both groups. In Step 2, compositional invariance, as shown in Table 8, the initial correlation between the composite scores for all constructs was 1.000; however, one construct "effort expectancy (EE)" had a permutation p-value of 0.009, which is below the threshold of 0.05. This implies that EE does not satisfy the compositional invariance condition. For all other constructs, the permutation P-values were above 0.05: BI=0.296, FC=0.182, PE=0.224, SI=0.237 and UB=0.123, which means that compositional invariance was successfully demonstrated for these constructs. Since both configural and compositional invariance are required to confirm partial measurement invariance, only five of the six constructs (BI, PE, SI, FC, and UB) met this condition. EE did not fulfill the condition of partial measurement invariance. Consequently, comparisons of EE between different ethnic groups should not be interpreted as any group differences, as these may be due to differences in measurement rather than true structural variance [41].

In Step 3a, the mean differences were significant for all constructs with p-values well below 0.05, including EE ($p = 0.010$), PE ($p = 0.000$), BI ($p = 0.008$), FC ($p = 0.000$), SI ($p = 0.029$), and UB ($p = 0.000$), indicating no equality of means. However, step 3b showed that the differences in variance were not statistically significant for any construct, with all p-values well above 0.05 (BI = 0.484, EE = 0.470, FC = 0.287, PE = 0.235, SI = 0.306, UB = 0.246). These results confirm that full measurement invariance was not achieved, although partial invariance (except for EE) was sufficient to allow valid path comparisons for the other constructs.

Table 8. MICOM results for ethnic group

Constructs	Configural invariance (Same algorithms for both groups)	Compositional invariance		Partial measurement invariance established	Equal mean assessment			Equal variance assessment			Full measurement invariance established
		C=1	C.I		Diff.	C.I	Equal	Diff.	C.I	Equal	
EE	Yes	1.000	[1.000; 1.000]	No	0.257	[-0.185; 0.179]	No	0.019	[-0.314; 0.335]	Yes	No
PE	Yes	1.000	[1.000; 1.000]	Yes	0.352	[-0.188; 0.178]	No	-0.148	[-0.340; 0.361]	Yes	No
SI	Yes	1.000	[1.000; 1.000]	Yes	0.206	[-0.182; 0.175]	No	0.091	[-0.260; 0.287]	Yes	No
FC	Yes	1.000	[1.000; 1.000]	Yes	0.433	[-0.183; 0.182]	No	-0.109	[-0.329; 0.357]	Yes	No
BI	Yes	1.000	[1.000; 1.000]	Yes	0.267	[-0.184; 0.180]	No	0.012	[-0.333; 0.366]	Yes	No
UB	Yes	1.000	[1.000; 1.000]	Yes	0.393	[-0.183; 0.178]	No	-0.135	[-0.340; 0.362]	Yes	No

The MGA comparison of structural path coefficients between majority and minority ethnic groups using Henseler's MGA and permutation tests is shown in Table 9. Of the six hypothesized paths, only PE → BI showed a statistically significant difference. This path was significantly stronger for the majority group ($\beta = 0.594$) than for the minority group ($\beta = 0.114$), with a path difference of 0.480. This difference was statistically significant in both Henseler's MGA ($p = 0.013$) and the permutation test ($p = 0.018$), suggesting that performance expectancy has a greater influence on the intention to use OPS among ethnic majority respondents. All other paths (SI → BI, FC → BI, FC → UB and BI → UB) did not differ significantly between the groups, with both tests yielding p-values above 0.05. The path EE → BI should be excluded from the interpretation, as it was not possible to detect even partial measurement invariance for EE; therefore, any group differences in this relationship are potentially unreliable. As a result, of the hypotheses H2a to H2f, only H2b is supported.

Table 9. Multigroup analysis for ethnic group

Hypothesis	Path	Majority	Minority	Diff.	95% CI	Henseler's MGA (2-tailed)	Permutation Test (2-tailed)	Supported
H2a	EE → BI	-0.089	0.197	-0.286	[-0.315; 0.303]	0.051	0.067	No/No
H2b	PE → BI	0.594	0.114	0.480	[-0.375; 0.382]	0.013	0.018	Yes/Yes
H2c	SI → BI	0.277	0.320	-0.043	[-0.273; 0.267]	0.411	0.382	No/No
H2d	FC → BI	0.186	0.274	-0.088	[-0.386; 0.369]	0.334	0.368	No/No
H2e	FC → UB	0.335	0.356	-0.020	[-0.257; 0.252]	0.435	0.442	No/No
H2f	BI → UB	0.603	0.532	0.071	[-0.255; 0.261]	0.309	0.334	No/No

4-3-3- Residence

Again, the MICOM procedure for analyzing the residence groups began with step 1, in which configuration invariance was confirmed, as the same model specification and data treatment were applied in both groups. In step 2, compositional invariance was checked by permutation tests. In Table 10, all constructs (EE, PE, SI, FC, BI, UB) showed original correlations of 1.000, with permutation p-values well above the threshold of 0.05 (EE = 0.123, PE = 0.227, SI = 0.642, FC = 0.353, BI = 0.336, UB = 0.332), confirming compositional invariance for each construct. Since both configural and compositional invariance were found, partial measurement invariance was satisfied, allowing for a meaningful comparison of path coefficients between urban and rural groups.

However, step 3a (equality of means) and step 3b (equality of variances) also largely supported invariance. In step 3a, all permutation p-values for the differences in means were above 0.05 (BI = 0.076, EE = 0.085, FC = 0.050, PE = 0.319, SI = 0.450, and UB = 0.160), indicating that there was no statistically significant difference in the latent means. In step 3b, the equality of variance was also given for most constructs, except for SI, which was just below the significance threshold with a permutation value of 0.043. Thus, while SI showed some variance inequality, almost complete measurement invariance was achieved, which increases confidence in the interpretation of group comparisons.

Table 10. MICOM results for residence group

Constructs	Configural invariance (Same algorithms for both groups)	Compositional invariance		Partial measurement invariance established	Equal mean assessment			Equal variance assessment			Full measurement invariance established
		C=1	C.I		Diff.	C.I	Equal	Diff.	C.I	Equal	
EE	Yes	1.000	[1.000; 1.000]	Yes	-0.081	[-0.094; 0.096]	Yes	-0.073	[-0.182; 0.175]	Yes	Yes
PE	Yes	1.000	[1.000; 1.000]	Yes	0.029	[-0.095; 0.099]	Yes	-0.130	[-0.203; 0.188]	Yes	Yes
SI	Yes	1.000	[1.000; 1.000]	Yes	0.010	[-0.097; 0.096]	Yes	-0.161	[-0.156; 0.150]	No	No
FC	Yes	1.000	[1.000; 1.000]	Yes	0.097	[-0.096; 0.097]	Yes	-0.073	[-0.206; 0.196]	Yes	Yes
BI	Yes	1.000	[1.000; 1.000]	Yes	0.086	[-0.099; 0.099]	Yes	-0.186	[-0.208; 0.202]	Yes	Yes
UB	Yes	1.000	[1.000; 1.000]	Yes	0.059	[-0.095; 0.099]	Yes	-0.140	[-0.200; 0.185]	Yes	Yes

For the MGA results, both Henseler's MGA and the permutation test were used to assess the differences in the path coefficients (see Table 11). Two paths showed statistically significant differences between the urban and rural respondents. First, the relationship between effort expectancy (EE) and behavioral intention (BI) was significantly stronger in the rural group ($\beta = 0.308$) than in the urban group, where the coefficient was negative ($\beta = -0.020$). The difference of -0.328 was statistically significant in both Henseler's MGA and the permutation test ($p = 0.000$ for both). This result implies that the perception of ease of use significantly influences the intention to use OPS among rural residents, while this effect is absent or even negative among the urban population.

Second, the path from facilitating conditions (FC) to behavioral intention (BI) differed significantly between the two groups. It was stronger in urban areas ($\beta = 0.340$) than in rural areas ($\beta = 0.117$), with a difference of 0.223 that was significant in both Henseler's MGA ($p = 0.008$) and the permutation test ($p = 0.013$). This indicates that urban respondents are more responsive to support resources in their intention to use OPS. The remaining paths – PE → BI, SI → BI, FC → UB and BI → UB – showed no statistically significant differences between the urban and rural groups, as both the p-values of Henseler's MGA and the permutation test were above 0.05. Consequently, only hypotheses 3a and 3d are supported, hypotheses 3b, 3c, 3e, and 3f are not supported.

Table 11. Multigroup analysis for residence group

Hypothesis	Path	Urban	Rural	Diff.	95% CI	Henseler's MGA (2-tailed)	Permutation Test (2-tailed)	Supported
H3a	EE → BI	-0.020	0.308	-0.328	[-0.150; 0.154]	0.000	0.000	Yes/Yes
H3b	PE → BI	0.437	0.282	0.155	[-0.169; 0.170]	0.051	0.071	No/No
H3c	SI → BI	0.169	0.241	-0.072	[-0.139; 0.141]	0.182	0.199	No/No
H3d	FC → BI	0.340	0.117	0.223	[-0.162; 0.166]	0.008	0.013	Yes/Yes
H3e	FC → UB	0.340	0.260	0.080	[-0.127; 0.130]	0.155	0.152	No/No
H3f	BI → UB	0.546	0.656	-0.109	[-0.128; 0.124]	0.079	0.079	No/No

5- Discussion

This study aimed to explore demographic differences in the acceptance and use of OPS in Vietnam, and in particular, how gender, ethnicity, and residence influence the key relationships in the UTAUT model through a multi-group analysis. The overall results, as illustrated in Figure 3, showed significant differences in selected relationships: gender showed a significant difference in the effect of social influence on behavioral intention; ethnicity differed in the effect of performance expectancy on behavioral intention; and place of residence showed differences in how effort expectancy and facilitating conditions affected behavioral intention. Critical to the study were the persistent limitations in the accessibility, usability, and effectiveness of Vietnam's OPS, which particularly affect disadvantaged demographic groups such as the rural population, ethnic minorities, and women. Given the gaps identified in the national review and previous literature, this study addresses the lack of systematic comparative analyses in the Vietnamese e-government context.

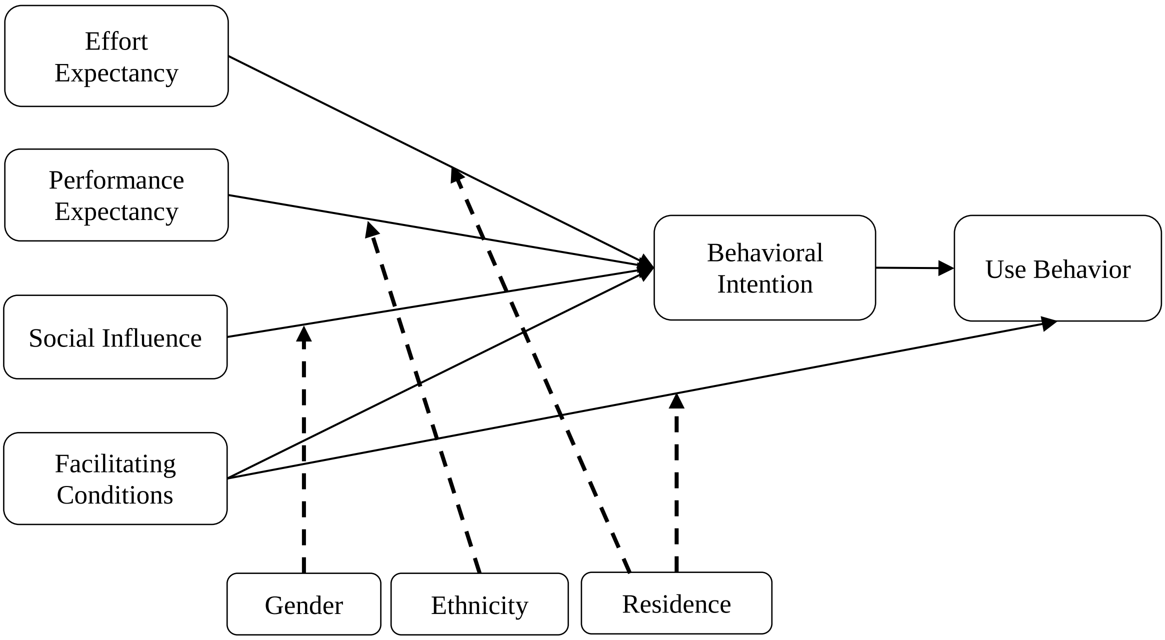

Figure 3. Result of multigroup analysis for different demographic groups

5-1- Gender Differences in OPS Adoption

The observed gender difference in social influence indicates that women's decisions to use OPS are more strongly shaped by family and community encouragement, reflecting social norms in which collective expectations often guide women's choices. Multiple studies have shown that women's e-government adoption and participation are significantly influenced by social ties, while men's adoption is driven by other factors. Previous research has agreed that women are more responsive to social influences in digital decision-making contexts, particularly under conditions where the use of a system is socially visible or normatively valued [7]. Studies from Colombia, Ethiopia, and Europe have shown that subjective norms and social networks significantly influence women's digital behavior, particularly in the areas of e-government and institutional technologies [12, 47-49]. Another study found that external encouragement promotes women's e-government usage behavior more than men's [9]. This may be because women are more influenced by family, friends, and community than men, and it is this closeness that shapes women's intention to use e-government services [48]. Women are more likely to be active e-government users when they engage in offline social networks, especially through their social relationships, whereas no such significant relationship was found for men [49]. These findings converge with the current study's observation that in collectivist cultures, such as Vietnam, family and community endorsement plays an essential role in promoting women's engagement with new technologies, including OPS.

From a policy perspective, these results call for gender-sensitive interventions that recognize the social embeddedness of women's digital behaviors. Rather than treating women as isolated users, e-government initiatives should harness existing social structures and trust networks to promote technological acceptance. Governments and local authorities can collaborate with women's unions, self-help groups, and community-based organizations to design communication strategies that emphasize social benefits and collective empowerment through OPS. Peer-to-peer mentoring programs, where digitally literate women act as local ambassadors, have proven effective in similar contexts by building competence and confidence within trusted networks. In addition, embedding e-government into existing services that are frequently used by women (e.g., health clinics, schools, or vocational training centers) can improve visibility and reduce the perceived risk of adoption. Such gender-sensitive and community-oriented strategies can foster stronger social support networks and accelerate women's engagement with e-government platforms.

5-2- Ethnicity Differences in OPS Adoption

The results of ethnic differences reveal that performance expectancy (PE) "the belief that using OPS will deliver tangible benefits" plays a stronger role among ethnic majority citizens than among minority groups. This finding highlights a persistent digital and perceptual divide that goes beyond access to technology and reflects deeper sociocultural and institutional disparities. One key explanation for this is the difference in digital readiness and trust in institutions. Other studies found that ethnic majority users, who are more likely to live in urban or economically developed regions, tend to have higher educational attainment, better access to broadband infrastructure, and more frequent interactions with government agencies [50, 51]. These conditions allow them to more easily recognize the utility of the OPS in saving time, reducing bureaucratic procedures, and providing convenient access to public services. In contrast, ethnic minority citizens, often residing in remote, mountainous, or border regions, may view such systems as distant, abstract, or irrelevant to their immediate needs. Limited digital literacy and linguistic barriers further reduce their ability to perceive and experience the benefits of digital government platforms.

This pattern is consistent with earlier studies in other developing countries. A multi-case study found that minority and low-literacy groups in developing countries in South Asia and Africa often undervalue e-services because of their limited exposure to successful digital experiences and a lack of confidence in the reliability of public digital systems [52]. The results also affirm another study that trust deficits and cultural unfamiliarity with formalized digital interactions reduced the performance expectancy of e-services among marginalized communities [21]. These studies suggest that performance expectancy is not only a cognitive judgment about usefulness but also a reflection of one's broader socio-institutional environment and cultural alignment with the government systems. In Vietnam, ethnic minority groups account for approximately 14.6% of the population but are disproportionately concentrated in areas with weak connectivity, lower service coverage, and diverse languages, that complicate administrative communication [53]. In addition, Vietnamese minority users often associate government systems with bureaucratic inefficiency or a lack of local representation, weakening their motivation to use digital channels [54]. Without evidence that digital platforms will lead to fairer or faster outcomes, performance expectancy remains low, regardless of access or awareness.

Together with earlier studies, this finding reaffirms that perceptions of performance expectancy among minority groups remain fragile and are often shaped by broader social and institutional inequalities. Many ethnic minority citizens continue to question whether e-government services deliver efficiency, convenience, and performance improvements in practice. Their skepticism may stem from several factors: prior experiences with bureaucratic inefficiency, language barriers complicating the use of online forms, and limited evidence that digital services yield concrete benefits in their local contexts. This distrust undermines the motivation to accept OPS among minority communities in Vietnam.

To address these issues, interventions must focus on demonstrating the practical value of OPS in ways that are both visible and locally relevant. Governments can deploy targeted awareness campaigns that showcase real examples of how digital services simplify administrative processes or save time and costs for local users. Pilot programs implemented within minority communities, supported by trusted local leaders or ethnic organizations, can serve as proof-of-concept initiatives that visibly validate the utility of these systems. Providing bilingual or multilingual service interfaces can also reduce the cognitive and linguistic barriers that inhibit perceived ease and performance. Training programs that focus on demonstrating concrete results rather than abstract technical skills can also shift perceptions from skepticism to appreciation. Moreover, performance expectancy among minorities can be strengthened by integrating OPS with tangible local benefits, such as agricultural support systems, healthcare scheduling, or small business registration. When OPS are directly linked to outcomes that improve livelihood and welfare, users are more likely to perceive them as being efficient and valuable.

5-3- Residence Differences in OPS Adoption

The multigroup analysis revealed two statistically significant distinctions between urban and rural respondents: the effect of effort expectancy (EE) and facilitating conditions (FC) on behavioral intention (BI). Both relationships highlight the dual-layered dynamic of digital inequality in Vietnam: one rooted in usability and the other in systemic support structures.

The first key finding shows that effort expectancy plays a much stronger role in shaping the intention to use online public services among rural users ($\beta = 0.308$) than among urban users ($\beta = -0.020$). This result suggests that ease of use and simplicity of interaction are crucial determinants for rural citizens, many of whom possess limited digital literacy and fewer prior experiences with OPS. Earlier studies also agreed that perceived ease of use is a critical factor in user satisfaction and the intention to use e-government services, especially among users with limited digital literacy [24, 25]. Rural users in Vietnam often engage with digital systems through mobile devices rather than computers, and are frequently constrained by low bandwidth or unstable connections [50]. Therefore, ease of use is so important that if e-government platforms are overly complex or service portals are not optimized for mobile use, the perceived effort increases dramatically for rural users. This result is similar to that found in a previous study in China, where ease of navigation, clarity of information, and mobile accessibility were the strongest predictors of adoption among rural citizens. These results emphasize that effort expectancy is not only a technical issue but also a psychological factor; it represents confidence in one's ability to engage effectively with the system. For many rural Vietnamese, where digital literacy programs remain limited, perceived difficulty can quickly translate into avoidance behavior, regardless of the potential benefits of OPS use.

The second major finding concerns the facilitating conditions. Urban users showed a significantly stronger relationship between FC and BI (β = 0.340) than rural users (β = 0.117). This corroborates the findings of previous studies that urban users have the necessary knowledge and resources to use e-government services, while these factors are weaker or missing in rural settings [24, 25, 55]. In rural areas, even when users are willing to engage, limited internet coverage, inadequate digital infrastructure, and low levels of digital literacy often erode confidence in the use of e-government services [50]. A case study focusing on China highlighted that rural regions continue to face unresolved issues concerning the affordability of technology and the enhancement of digital literacy. Similar to China and Nigeria, rural users in Vietnam often rely on internet cafés or mobile phones to access online services, leading to higher usage costs than home-based connections and shorter overall usage time [55, 56]. In line with other studies on e-government experiences, this study affirms that internet users in rural areas often have less familiarity with digital platforms, which further hinders their ability to engage effectively with OPS [24, 57-60].

The difference between urban and rural dwellers in terms of the impact of effort expectancy and facilitating conditions on behavioral intention highlights the profound impact of infrastructural and contextual differences on OPS adoption. This realization is particularly important in Vietnam, where two-thirds of the population lives in rural areas. These populations often have lower levels of digital literacy and less access to institutional support; therefore, their concerns about usability and support are not just subjective preferences but rather a well-founded reflection of persistent systemic disadvantages. To mitigate digital disparities in rural areas, e-government systems should prioritize usability by implementing simplified interfaces, ensuring mobile accessibility, and optimizing low-bandwidth environments. Rural users particularly benefit from intuitive designs that require minimal prior digital experience. Concurrently, it is essential to enhance the facilitating conditions. This entails expanding reliable internet access and establishing local support structures, such as village-level digital help centers, ICT volunteers, and community-based digital literacy programs in schools or cooperatives. Furthermore, hybrid service models that integrate online and offline support can serve as transitional solutions, enabling rural residents to build digital confidence while maintaining access to essential services.

6- Conclusion

This study aimed to uncover how gender, ethnicity, and place of residence shape citizens' acceptance and use of OPS in Vietnam, a country navigating the early stages of digital transformation. Using the UTAUT framework and rigorous multigroup analysis, this study revealed that citizens' technology adoption behaviors are far from homogeneous. Gender moderates the role of social influence: women's intentions to use OPS are more strongly guided by family and community expectations. Ethnicity emerged as another dividing line, with the majority of users placing greater trust in the usefulness and efficiency of OPS, while minority users remained less convinced of its practical benefits. Meanwhile, the contrast between urban and rural populations underscored the digital divide that persists across infrastructure, literacy, and institutional support, rural residents were more affected by how easy OPS was to use, while urban users responded more to the availability of supportive conditions. Collectively, these findings challenge the assumption that citizen interactions with digital government services follow a single, uniform pathway. Instead, they highlight the deep social, cultural, and structural dimensions that mediate how different groups experience the promise of digital government. Beyond its empirical findings, this study has important implications. This shows that effective digital transformation is not simply about deploying technology but about embedding it within social realities. For women, this study suggests that leveraging social networks, women's unions, and peer-learning initiatives can amplify trust and engagement. Among ethnic minorities, the limited influence of performance expectancy reveals deeper skepticism toward government-provided digital services, which can only be addressed through visible demonstrations of efficiency, reliability, and cultural sensitivity.

For rural users, policies must go beyond improving connectivity; they must focus on simplifying interfaces, ensuring affordability, and building localized digital support systems. These insights extend the UTAUT model by integrating social and contextual variables and serve as a practical guide for policymakers striving for inclusive governance. By aligning service design with the lived experiences of diverse user groups, Vietnam and similar developing economies can move closer to the vision of a digital government that truly serves all citizens, not just the digitally privileged. However, this study has some limitations. The cross-sectional nature of the data constrains causal inference, and Vietnam's specific cultural and administrative environment may limit generalizability beyond its borders to other countries. Moreover, the analysis focused on selected demographic variables, while other potentially influential factors, such as income, education, and occupation, remain unexplored. Addressing these gaps presents a rich agenda for future studies. Longitudinal studies could track how demographic differences evolve over time as digital literacy and infrastructure improve, while comparative cross-country analyses could situate Vietnam's experience within broader regional and global trends. Furthermore, qualitative investigations may help uncover the underlying perceptions and narratives that quantitative models cannot fully capture. As governments worldwide advance their digital agendas, understanding not only who adopts but also why and how different groups adopt will become increasingly vital. By highlighting the social fabric behind digital behavior, this study opens new ground for designing e-government systems that are equitable, trusted, and resilient, systems that do not simply digitize bureaucracy but re-imagine citizenship in the digital era.

7- Declarations

7-1- Author Contributions

Conceptualization, V.B.N.; methodology, T.M.D.N.; software, T.M.D.N.; validation, T.M.D.N.; formal analysis, T.M.D.N.; investigation, V.B.N.; resources, V.B.N.; data curation, T.M.D.N.; writing—original draft preparation, T.M.D.N.; writing—review and editing, V.B.N.; visualization, T.M.D.N.; supervision, V.B.N.; project administration, V.B.N.; funding acquisition, V.B.N. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding

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7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Not applicable.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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