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Policy Shock and Fintech Adoption: Extending UTAUT2 with Policy Trust to Explain SME Mobile Money Usage Post E-Levy Repeal in Ghana

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Abstract:

Research Aims:
This study set out to extend UTAUT2 through the construct of policy trust, examining how it shapes behavioral intention and use behavior around mobile money among Ghanaian MSMEs after the E-Levy's repeal. Policy trust was tested in two roles—as a direct predictor and as a moderator.

Methodology:
The study followed a quantitative explanatory approach, running a cross-sectional survey with 400 MSMEs across Accra, Kumasi, and Sekondi-Takoradi through purposive sampling. Analysis relied on PLS-SEM in SmartPLS 4.0, covering the measurement model, structural model, and a two-stage moderation test.

Research Findings:
As many as 11 out of 12 hypotheses were supported. Performance expectancy, effort expectancy, hedonic motivation, price value, and habit significantly influence behavioral intention, while social influence does not. Facilitating conditions and habit influence use behavior, with behavioral intention as the strongest predictor. Policy trust significantly affects behavioral intention and also moderates two main relationships. The model explains 61.2% of behavioral intention and 68.7% of use behavior.

Theoretical Contribution/Originality:
This study introduces policy trust as an extension of UTAUT2, built on an integration with policy feedback theory. Policy trust proved significant for usage intention, and it also moderated two key relationships—price value to behavioral intention, and facilitating conditions to use behavior. UTAUT2 gains an institutional dimension it previously lacked.

Practitioners/Policy Implications:
Several recommendations follow from these findings. Bank of Ghana and the Ghana Revenue Authority should strengthen policy communication. Mobile money providers need to pair infrastructure investment with cost certainty. And Fintech Growth Fund administrators would benefit from factoring policy trust into how they segment beneficiaries.

Research Limitations/Implications:
This study has its constraints—a cross-sectional design, self-report data, a sample limited to urban areas, and a policy trust construct still awaiting broader validation. Future work could take a longitudinal approach, extend the analysis across countries, and draw on actual transaction data rather than survey responses alone.

Keywords: UTAUT2, Policy Trust, Mobile Money, E-Levy, MSME, PLS-SEM, Ghana.

INTRODUCTION

Across Sub-Saharan Africa, the rise of digital payments has turned mobile money into a key driver of financial inclusion, extending financial access to communities that formal banks have historically left behind. The GSMA (2026) reports that global mobile money transactions are expected to reach a value of USD 2 trillion by 2025, with Sub-Saharan Africa alone responsible for more than half of that amount and home to upwards of one billion registered accounts. Ghana offers a clear example: mobile money there has grown beyond its original purpose as a money-transfer service to become indispensable transactional infrastructure for MSMEs, many of which continue to face obstacles in accessing conventional banking (Coffie et al., 2021). Given that MSMEs serve as the backbone of the country's economy, the pace at which this sector takes up financial technology has a direct effect on overall financial inclusion (Krah et al., 2024). At the same time, this adoption process is not immune to outside influence—government fiscal policy and regulatory frameworks play a substantial role, sometimes encouraging mobile money use and at other times constraining it (Dodoo et al., 2025). It is this dynamic that makes the link between digital fiscal policy and MSMEs' uptake of financial technology in Ghana such an important area of inquiry, offering insight into how shifting policies affect user trust and the choices people make around digital financial services.

Ghana's rollout of the 1.5% Electronic Transfer Levy (E-Levy) in May 2022 offers perhaps the most telling backdrop for understanding mobile money adoption in the country. It wasn't just another tax measure. The levy reshaped how people engaged with digital services altogether—mobile money transaction values dropped by 47%, transaction counts fell by 24%, and cross-operator transactions declined by 49% (Takyi, 2024). Public pushback followed quickly and stayed strong; by 2024, 79% of Ghanaians favored scrapping the tax entirely (Afrobarometer, 2024). The government eventually gave in. On April 2, 2025, it repealed the E-Levy through the Electronic Transfer Levy (Repeal) Act (Ghana Revenue Authority, 2025). Less than three years separated the levy's introduction from its reversal. Few countries offer such a compressed, clear-cut window into how fiscal policy can reshape financial technology adoption.

The numbers after the E-Levy's repeal tell an interesting story. Mobile money usage bounced back—but not just because transaction costs dropped. MSME operators also seemed to shed some of the psychological hesitation that had built up around digital payments (News Ghana, 2026). Transaction value climbed to GH¢2.36 trillion by October 2024, a 55% jump from the year before (News Ghana, 2026). Something more than technology's raw appeal was driving this recovery. Trust in government policy mattered too. Baah-Peprah et al. (2024) back this up, showing that how much people trust their government meaningfully shapes their willingness to adopt fintech, particularly around electronic taxation. Conventional models of technology adoption struggle to capture this. Ghana's SMEs, in the wake of the E-Levy repeal, seem to call for a broader, more comprehensive framework for understanding technology acceptance.

This study draws on the UTAUT2 model to explain why MSMEs adopt mobile money, largely because the framework was built specifically to capture technology acceptance at the consumer level (Venkatesh et al., 2012). According to this model, several factors shape both the intention to use technology and actual usage behavior: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit (Venkatesh et al., 2012; Dwivedi et al., 2019). Evidence from Ghana lends support to this approach. Several studies have found that performance expectancy, effort expectancy, price value, and facilitating conditions all significantly influence how MSME operators take up mobile money (Penney et al., 2021; Dodoo et al., 2025). UTAUT2, then, fits naturally as the guiding framework here.

UTAUT2 does a solid job explaining technology adoption, but it assumes a stable policy environment. That assumption leaves a gap—the model can't really capture how shifts in fiscal policy affect user behavior. Policy feedback theory fills part of this gap. It holds that public policy actively shapes how people perceive and behave, which means the E-Levy's introduction and later repeal likely left a mark on user trust (Pierson, 1993). Baah-Peprah et al. (2024) found that trust in government significantly affects fintech adoption. Mensah et al. (2022), meanwhile, showed that UTAUT alone falls short in explaining how the E-Levy affected mobile money usage. This gap is precisely why the current study proposes policy trust as an extension to UTAUT2.

Research on trust and technology adoption paints a mixed picture. Some studies point to a clear link between trust and mobile payment use (Hashim et al., 2020; Shao et al., 2019). Others find no effect at all, or results that contradict each other outright (Belanger et al., 2002; Lew et al., 2020; Tian & Chan, 2024). These inconsistencies hint at something UTAUT2 hasn't quite captured—how policy changes reshape the very sources of user trust. Policy trust may be the missing piece. This study treats it as a distinct construct, one better suited to explaining fintech adoption when government policy is in flux.

Findings on UTAUT2's determinants in digital payments are just as inconsistent. Facilitating conditions, for instance, show a significant effect on adoption in some studies but not in others (Alalwan et al., 2017; Kwateng et al., 2018; Andrianto, 2020; Arviana et al., 2022; Wibowo & Arviansyah, 2023). Price value and trust tell a similar story. Their effects shift depending on whether researchers use PLS-SEM or ANN approaches (Dodoo et al., 2025). Taken together, these patterns suggest that relationships among UTAUT2 variables aren't fixed—they depend on context, and likely work through indirect pathways rather than direct ones. Policy trust may be one such pathway. This study positions it as a mediating variable, linking UTAUT2's core determinants to the intention to use mobile money in the aftermath of a fiscal policy shift.

UTAUT2 has been extended to include trust constructs many times over, yet most of this work centers on digital banking consumers operating in fairly stable policy settings (Alalwan et al., 2018; Tian & Chan, 2024; Khoa, 2024). Ghana's mobile money literature hasn't quite caught up. No study has specifically looked at what happened after the E-Levy's repeal, nor examined the role policy trust plays among MSMEs (Penney et al., 2021; Dodoo et al., 2025). Mensah et al. (2022) came close, but their work looked at the E-Levy while it was still active—not in its aftermath. A clear gap remains. No one has yet studied how Ghanaian SMEs adopted mobile money after the E-Levy's repeal through an UTAUT2 framework expanded with policy trust. This study steps into that gap.

Prior research also runs into methodological limits. Takyi (2024) relied on aggregate data, which can't really get at the psychological mechanisms playing out at the level of individual business operators. Most UTAUT2-based studies face a different problem—their cross-sectional designs struggle to capture how perceptions shifted once the E-Levy was repealed (Penney et al., 2021; Krah et al., 2024). Dodoo et al. (2025) came closer, applying a PLS-SEM-ANN approach, but even their model left out the policy-change dimension entirely. This study takes a different route. It uses SmartPLS 4.0 to test an expanded model, one built specifically for the post-repeal context.

Put these four gaps together, and one thing becomes clear: no study has examined UTAUT2 extended with policy trust to explain how Ghanaian SMEs adopted mobile money after the E-Levy repeal, using PLS-SEM, across all four dimensions at once—construct, population, timing, and method. Leaving this gap unaddressed carries real theoretical costs. UTAUT2 would keep operating as a model blind to policy shocks. Its predictive power would keep eroding, especially in developing countries where digital fiscal regulations shift often and hit hard.

The practical stakes are just as high. Without a sharp understanding of how policy trust reshapes intentions and behavior, policymakers and digital finance providers risk repeating old mistakes. They might assume that removing cost barriers alone restores trust among MSME operators. But residual distrust from past policy experiences doesn't simply vanish—it can linger and quietly undermine adoption for years. These stakes set up the objectives and research questions that follow.

Leave this gap unaddressed, and UTAUT2 will keep producing shaky, inconsistent predictions wherever digital fiscal policy keeps shifting—which is exactly the reality in most developing countries. There's a practical risk here too. Assuming that lower costs alone will drive mobile money adoption overlooks something important: low policy trust among MSMEs (Fintech Times, 2026; ICLG, 2026). And MSMEs matter enormously in Ghana. They make up roughly 92% of business units, employ 80% of the workforce, and generate 60% of GDP (UNCDF, UNDP, & UNCTAD, 2026).

This is precisely why policy trust deserves attention. Ghana is currently moving past crisis recovery, into a longer phase of fiscal and financial reform backed by the IMF (IMF, 2026). MSME operators, having lived through the E-Levy experience, need real assurance that government policy will stay consistent going forward. Policy trust sits at the center of that assurance. Examining it in the post-repeal period matters on two fronts—it helps explain actual adoption behavior, and it adds something new to how we think about technology acceptance theory more broadly.

This study builds directly on the work of Dodoo et al. (2025) and Mensah et al. (2022), but pushes the conversation forward in three ways. First, it develops policy trust—not generic trust—as the specific extension to UTAUT2. Second, it's set in the post-repeal period of the E-Levy, capturing how trust actually shifted once the policy changed. Third, it zeroes in on Ghanaian SMEs, the group that felt the E-Levy's implementation and repeal most directly.

Taken together, these three moves let the study extend UTAUT2 through policy feedback theory, treating policy trust as the mechanism that explains mobile money adoption amid fiscal policy shifts. The theoretical contribution here matters. Once policy trust enters the picture, the policy environment stops being treated as a stable, external backdrop. If the construct proves significant, it could bridge two literatures that rarely speak to each other—technology acceptance and policy feedback—while also explaining why SMEs adopt mobile money the way they do after fiscal policy changes. This isn't simply UTAUT2 repeated. It's UTAUT2 extended, built to handle technology adoption in policy environments that don't sit still.

This study sets out to test how UTAUT2's determinants shape behavioral intention and actual use of mobile money among Ghanaian MSMEs, alongside testing policy trust as an extension of the model in the post-E-Levy repeal context. Theoretically, it extends UTAUT2 by folding in policy feedback theory, aiming to explain the role policy trust plays in technology adoption. There's a practical side too. The findings are meant to inform governments, mobile money providers, and financing program managers as they design policies and strategies that support digital service adoption. To get there, the study takes a quantitative explanatory approach, using PLS-SEM (SmartPLS 4.0) with Ghanaian MSME operators as the study population.

METHODS

This study follows a positivist paradigm, using a quantitative explanatory approach to empirically test how UTAUT2 determinants, policy trust, behavioral intention, and mobile money use behavior relate to one another (Creswell & Creswell, 2018; Hair et al., 2022). Data collection followed a cross-sectional survey design, timed specifically for the post-E-Levy repeal period so respondents' perceptions would reflect the full policy experience—not just fragments of it (Sekaran & Bougie, 2020). This design fits the task at hand. It's well-suited for testing complex structural models, and it directly addresses the methodological gaps left by earlier research.

The study population is made up of Ghanaian MSME operators who use mobile money for business transactions. SMEs were the natural choice here—they dominate Ghana's economic structure, accounting for 92% of business units, and they're also the group hit hardest by the E-Levy's rise and fall (Registrar General's Department, 2023; Coffie et al., 2021).

No complete sampling frame exists for this population, so sample size was calculated using Cochran's (1977) formula for infinite populations, at a 95% confidence level and 5% margin of error. That works out to a minimum of 384 respondents. To account for invalid or incomplete responses, the study set its target slightly higher, at 400.

Purposive sampling was the method of choice, again due to the absence of a sampling frame, but also because respondents needed direct, hands-on experience with mobile money (Etikan et al., 2016). Specifically, eligible respondents are MSME owners or managers who had already been using mobile money before April 2025, had been operating their business for at least a year, and were based in major economic hubs—Accra, Kumasi, or Sekondi-Takoradi. These criteria weren't arbitrary. They were designed to ensure respondents had genuinely lived through the E-Levy's policy transition and could speak meaningfully to their own sense of policy trust.

Here's how each operational variable in this study is defined. **[1] Performance expectancy** captures MSME operators' belief that mobile money genuinely helps their business run better (Venkatesh et al., 2012). Two dimensions sit underneath this—usefulness and operational efficiency—measured through three indicators: faster transaction processing, better cash flow management, and progress toward sales targets. These dimensions and indicators stay in the model because they've consistently proven to be the strongest predictors of mobile money adoption among Ghanaian SMEs (Penney et al., 2021). **[2] Effort expectancy** reflects how easy MSME operators find mobile money to use (Venkatesh et al., 2012). It splits into two dimensions—ease of learning and ease of operation—captured through three indicators: an interface that's simple to navigate, transactions that don't demand technical know-how, and smooth performance of the app or USSD system. Ghanaian research backs this up too, showing these factors do shape adoption among local SMEs (Krah et al., 2024).

[3] Social influence speaks to how much other people's opinions shape an MSME operator's decision to use mobile money (Venkatesh et al., 2012). Three indicators measure it: encouragement from fellow business owners, customer expectations around digital payments, and the informal norms that develop within trading communities. Social networks turn out to matter a great deal here—research on Ghanaian SMEs confirms as much (Coffie et al., 2021). **[4] Facilitating conditions** cover how MSME operators perceive the resources and infrastructure available to support mobile money use (Venkatesh et al., 2012). This variable rests on a resource-and-infrastructure-support dimension, measured through three indicators: how accessible mobile money agents are, how stable telecom networks are, and how much technical help is available when something goes wrong. This dimension stays in the model for a specific reason—differences in infrastructure may well explain why earlier studies produced conflicting results, and Ghana's context deserves its own test (Alalwan et al., 2017; Kwateng et al., 2018).

[5] Hedonic motivation describes the enjoyment or satisfaction MSME operators get from using mobile money (Venkatesh et al., 2012). It's built on an intrinsic-pleasure dimension, measured through three indicators: transactions that feel enjoyable, features that seem modern and appealing, and a sense that using mobile money enhances the business's image as technologically adaptive. This dimension fits naturally within UTAUT2's broader focus on individual-level user behavior (Venkatesh et al., 2012). **[6] Price value** reflects how MSME operators weigh the costs of mobile money against its benefits (Venkatesh et al., 2012). A single value-perception dimension covers this, measured through three indicators: transaction costs that feel worth it, costs lower than other payment options, and a sense that the E-Levy's repeal made mobile money more valuable to use. Price value earns particular attention here because it's the construct most directly shaken up by the E-Levy policy itself (Takyi, 2024).

[7] Habit describes how far mobile money use has settled into an automatic, routine behavior for MSME operators (Venkatesh et al., 2012). It's measured through three indicators: using mobile money as a standard part of transaction routines, doing so without conscious thought, and sticking with it even when other options are available. This dimension earns its place here because habit has been shown to sustain mobile money use even after major policy shifts (Dodoo et al., 2025). **[8] Policy trust** captures how much confidence MSME operators place in the government's credibility, consistency, and good faith when it comes to shaping digital fiscal policy that affects mobile money use. This construct draws on Mayer et al. (1995), Levi and Stoker (2000), and Baah-Peprah et al. (2024). Three dimensions make it up: policy credibility (believing the E-Levy repeal is truly permanent), regulatory consistency (believing similar levies won't resurface), and pro-MSME intent (believing policy genuinely accounts for MSME interests). These three dimensions were chosen because they reflect the mechanics of policy feedback (Pierson, 1993), offering an early attempt at operationalizing policy trust within African mobile money research.

[9] Behavioral intention captures whether MSME operators plan to keep using mobile money going forward (Venkatesh et al., 2012). It rests on a usage-intention dimension, measured through three indicators: intent to continue using mobile money, willingness to recommend it to other business owners, and plans to use it more heavily in daily operations. This dimension holds a central place in the model, since behavioral intention functions as UTAUT2's key mediating variable. **[10] Use behavior** measures what MSME operators actually do—not just what they intend. It's built on a usage-behavior dimension, measured through three indicators: how often transactions occur, what share of business transactions run through mobile money, and how long it's been used for business purposes. These indicators were chosen because they capture real, observed usage, following Venkatesh et al.'s (2012) own recommendations.

Data analysis relied on PLS-SEM using SmartPLS 4.0. Several reasons drove this choice: the method handles complex models well, it's geared toward prediction and the development of new constructs like policy trust, and it doesn't demand strict data normality (Hair et al., 2019; Hair et al., 2022). The analysis unfolded in two stages—first the outer model, then the inner model.

The outer model evaluation checks construct validity and reliability. Convergent validity comes from outer loadings (≥0.70) and AVE (≥0.50). Reliability, meanwhile, relies on Cronbach's Alpha and Composite Reliability, both expected to clear 0.70. Discriminant validity gets tested through HTMT (≤0.90). For the policy trust construct specifically, expert judgment was carried out beforehand to confirm content validity, well before the questionnaire went out (Hair et al., 2022; Henseler et al., 2015; DeVellis & Thorpe, 2021).

The inner model evaluation shifts focus to predictive strength and the relationships between constructs. This stage covers multicollinearity testing (VIF < 5), the coefficient of determination (R^2), effect size (f^2), and predictive relevance ($Q^2 > 0$). Hypothesis testing follows, using bootstrapping with 5,000 subsamples. Decisions rest on t-statistic values (≥1.96) alongside p-values (Hair et al., 2022; Chin, 1998; Cohen, 1988).

Policy trust's moderating effects (H11 and H12) were tested using a two-stage approach (Henseler & Chin, 2010). The first stage estimates latent scores. The second builds interaction terms—PT × PV and PT × FC—to test whether moderation reaches significance. From there, simple slope analysis reveals the direction of these moderating effects at both high and low levels of policy trust (Dawson, 2014).

RESULTS

Respondent Description

The final sample included 400 MSME operators using mobile money across Ghana. Data collection actually brought in 412 completed questionnaires. Twelve of those, though, had to go—either they didn't meet the study's criteria or showed clear signs of invalid responses. That left 400 usable responses, putting the response rate at 97.1%.

Table 1. Respondent Characteristics

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	218	54,5
	Female	182	45,5
Age	18–25 years	62	15,5
	26–35 years	158	39,5
	36–45 years	121	30,3
	Above 45 years	59	14,8
Business sector	Retail/trading	176	44,0
	Food and beverage	84	21,0
	Services	68	17,0
	Manufacturing/craft	45	11,3

Characteristic	Category	Frequency (n)	Percentage (%)
	Agriculture-related	27	6,8
Business age	Less than 3 years	121	30,3
	3–5 years	143	35,8
	6–10 years	92	23,0
	More than 10 years	44	11,0
Business location	Accra	168	42,0
	Kumasi	121	30,3
	Sekondi-Takoradi	111	27,8
Monthly transaction volume (mobile money)	Below GH¢2,000	89	22,3
	GH¢2,000–GH¢5,999	156	39,0
	GH¢6,000–GH¢10,000	98	24,5
	Above GH¢10,000	57	14,3
Mobile money provider used	MTN MoMo	287	71,8
	Telecel Cash	68	17,0
	AirtelTigo Money	45	11,3

Source: Primary Daya, 2026

Table 1 shows a fairly even split between male and female business owners, with most respondents falling into the 26–35 age bracket—Ghana's most economically active age group. Retail and trade dominate as the most common business type, which lines up with what we already know about Ghana's MSME landscape: small- and medium-scale trading has always been its backbone (Coffie, Hongjiang, Mensah, Kiconco, & Simon, 2021).

Business age tells its own story. Most respondents had been running their businesses for 3–5 years, meaning the majority were already operating before the E-Levy came into effect in 2022. That matters here. It means they lived through the policy's full arc—implementation and repeal alike—satisfying exactly the sample criteria this study set out to capture. As for location, respondents spread out fairly evenly across Ghana's three biggest mobile money hubs: Accra, Kumasi, and Sekondi-Takoradi.

Transaction frequency tells an interesting story too. Most respondents fell into the medium monthly transaction bracket (GH¢2,000–GH¢5,999), suggesting mobile money has become part of routine business operations rather than something reached for only occasionally. MTN MoMo's dominance as the go-to provider—used by 71.8 percent of respondents—lines up with what's already known about Ghana's mobile money landscape, where MTN MoMo holds a commanding market share nationally (Bank of Ghana, 2025).

Put simply, this respondent profile fits the study's target population well. These are active MSME operators who lived through the E-Levy's full policy cycle, and their transaction habits are frequent enough to make them a solid basis for studying adoption behavior.

Descriptive statistics

Descriptive statistics were used to map out how respondents answered across each construct, based on a 1–5 Likert scale (1 = strongly disagree, 5 = strongly agree). To make sense of these scores, mean values were sorted into three interval categories using a continuum approach: 1.00–2.33 for low, 2.34–3.67 for moderate, and 3.68–5.00 for high.

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Table 2. Descriptive Statistics of Research Constructs

Construct	Mean	Std. Devitiation	Min	Max	Category
Performance Expectancy (PE)	3.92	0.68	1.67	5.00	High
Effort Expectancy (EE)	3.85	0.71	1.33	5.00	High
Social Influence (SI)	3.54	0.79	1.00	5.00	Moderate
Facilitating Conditions (FC)	3.38	0.84	1.00	5.00	Moderate
Hedonic Motivation (HM)	3.61	0.75	1.00	5.00	Moderate
Price Value (PV)	3.77	0.70	1.67	5.00	High
Habit (HT)	3.95	0.65	2.00	5.00	High
Policy Trust (PT)	3.21	0.93	1.00	5.00	Moderate
Behavioral Intention (BI)	3.88	0.69	1,67	5.00	High
Use Behavior (UB)	3.83	0.72	1.33	5.00	High

Source: SEM PLS Output, 2026

Table 2 shows most of UTAUT2's core constructs landing in the high category. Habit tops the list (M = 3.95), closely followed by Performance Expectancy (M = 3.92). This tells us something specific: Ghanaian MSME operators haven't just adopted mobile money—they've built it into their daily transaction routine, and they genuinely feel its benefits. Penney, Agyei, Boadi, Abrokwah, and Ofori-Boafo (2021) found much the same in a comparable population.

Social Influence (M = 3.54) and Facilitating Conditions (M = 3.38) tell a different story, settling into the moderate range instead. Neither peer pressure from trade networks nor the availability of supporting infrastructure seems to carry the same weight as the more cognitive, functional determinants. This isn't entirely surprising—empirically, these particular factors tend to swing more depending on context.

Policy Trust came in lowest among all constructs (M = 3.21; SD = 0.93), and its variance was the highest too. That gap says something important—MSMEs' confidence in government fiscal policy hasn't fully bounced back, even with the E-Levy gone. Behavioral Intention (M = 3.88) and Use Behavior (M = 3.83) paint a different picture, both sitting comfortably in the high category. Intentions and actual mobile money use, it seems, are moving together here.

Measurement Model Evaluation (Outer Model)

Before moving into structural equation modeling, the measurement model was evaluated to confirm that every indicator held up in terms of validity and reliability. This covered convergent validity, internal consistency reliability, and discriminant validity.

1. **Convergent Validity**

   Convergent validity checks whether the indicators within a single construct are actually measuring the same underlying concept, consistently. Outer loading and Average

Variance Extracted (AVE) serve as the tests here. Higher values on both simply mean the indicators represent their construct more faithfully.

Table 3. Outer Loadings, Average Variance Extracted (AVE), and Reliability

Construct	Indicator	Outer Loading	AVE	Composite Reliability	Cronbach's Alpha
Performance Expectancy (PE)	PE1	0.842	0.670	0.859	0.812
	PE2	0.815			
	PE3	0.798			
Effort Expectancy (EE)	EE1	0.826	0.645	0.845	0.798
	EE2	0.803			
	EE3	0.779			
Social Influence (SI)	SI1	0.788	0.590	0.812	0.762
	SI2	0.771			
	SI3	0.744			
Facilitating Conditions (FC)	FC1	0.802	0.560	0.791	0.734
	FC2	0.756			
	FC3	0.681			
Hedonic Motivation (HM)	HM1	0.819	0.628	0.835	0.788
	HM2	0.795			
	HM3	0.762			
Price Value (PV)	PV1	0.834	0.648	0.846	0.801
	PV2	0.808			
	PV3	0.771			
Habit (HT)	HT1	0.851	0.684	0.867	0.821
	HT2	0.827			
	HT3	0.803			
Policy Trust (PT)	PT1	0.812	0.618	0.829	0.774
	PT2	0.789			
	PT3	0.756			
Behavioral Intention (BI)	BI1	0.847	0.675	0.862	0.815
	BI2	0.822			
	BI3	0.795			
Use Behavior (UB)	UB1	0.836	0.651	0.848	0.799
	UB2	0.809			
	UB3	0.774			

Source: SEM PLS Output, 2026

Table 3 shows nearly every outer loading clearing the 0.70 threshold. One exception stands out: FC3, which came in slightly below at 0.681. Hair, Hult, Ringle, and Sarstedt (2022) offer useful guidance here—indicators in the 0.40–0.70 range don't automatically need to go, especially if dropping them wouldn't meaningfully boost AVE or Composite Reliability beyond what's already been achieved. That's exactly the situation with FC3. The Facilitating Conditions construct still held an AVE above 0.50 (0.560) even with FC3 left in place. So it stayed, partly because of that statistical case, but also because of what it captures—technical assistance availability is too central to the facilitating conditions concept to drop lightly.

Every construct cleared AVE values above 0.50 and Composite Reliability above 0.70, which together confirm convergent validity and internal reliability across the board (Hair et al., 2022). One result deserves particular attention. Policy Trust—the new construct introduced in this study—posted an AVE of 0.618 and CR of 0.829, numbers right in line with the well-established UTAUT2 constructs. That's a meaningful signal. Even without a track record of prior empirical validation, this new construct appears to be psychometrically sound.

2. **Discriminant Validity**

The goal here is straightforward: confirm that each construct stands apart empirically from the others. HTMT handled this test. Values below 0.90 mean each construct is measuring something genuinely distinct, with no real overlap between them.

Table 4. Heterotrait-Monotrait Ratio (HTMT) Matrix

Construct	PE	EE	SI	FC	HM	PV	HT	PT	BI
EE	0.687								
SI	0.542	0.581							
FC	0.478	0.512	0.556						
HM	0.601	0.634	0.598	0.487					
PV	0.658	0.612	0.523	0.501	0.577				
HT	0.712	0.695	0.548	0.534	0.601	0.664			
PT	0.412	0.398	0.445	0.521	0.387	0.556	0.423		
BI	0.756	0.732	0.612	0.589	0.678	0.741	0.788	0.612	
UB	0.701	0.688	0.567	0.734	0.623	0.698	0.812	0.578	0.823

Source: SEM PLS Output, 2026

Table 4 confirms every HTMT value stays below 0.90, meeting the discriminant validity requirement across the board (Henseler et al., 2015). Two pairs came closest to the threshold: Behavioral Intention–Use Behavior at 0.823 and Habit–Use Behavior at 0.812. Neither crossed the line, though. Policy Trust, meanwhile, sits noticeably lower than every other UTAUT2 construct, with HTMT values ranging from 0.387 to 0.556. That gap makes a clear case for its empirical distinctiveness from the rest of the UTAUT2 determinants.

With convergent validity, reliability, and discriminant validity all holding up, the measurement model (outer model) is ready to move forward. The next step is evaluating the structural model (inner model).

Structural Model Evaluation (Inner Model)

Once the measurement model proved valid and reliable, the analysis moved on to the structural model. This stage assesses how strong the relationships between constructs really are, along with the model's overall predictive power. It covers multicollinearity testing, the coefficient of determination, effect size, and predictive relevance.

1. **Multicollinearity Test (Variance Inflation Factor)**

The goal here is to make sure the predictor constructs (exogenous variables) don't overlap too much or correlate too strongly with one another. Here's why that matters: if two predictors end up measuring nearly the same thing—Habit and Behavioral Intention explaining overlapping ground, for instance—the resulting path coefficients become unstable and hard to interpret accurately. One predictor might look insignificant not because it truly has no effect, but because a similar predictor quietly absorbed its influence. VIF exists precisely to catch this. It confirms that each predictor is contributing something genuinely unique to the model.

Table 5. Collinearity statistics (VIF)

Predictor	VIF (→ BI)	VIF (→ UB)
Performance Expectancy (PE)	1.842	-
Effort Expectancy (EE)	1.756	-
Social Influence (SI)	1.523	-
Hedonic Motivation (HM)	1.678	-
Price Value (PV)	1.891	-
Habit (HT)	2.134	1.987
Policy Trust (PT)	1.612	-
Facilitating Conditions (FC)	-	1.745
Behavioral Intention (BI)	-	2.056

Source: SEM PLS Output, 2026

Table 5 shows every VIF value sitting comfortably below the threshold of 5. The highest figures appear on two paths—Habit to BI at 1.834, and Behavioral Intention to UB at 2.056. Still, both fall well within acceptable range. This rules out any serious multicollinearity problem among the exogenous constructs. As a result, the path coefficients produced during bootstrapping can be trusted—no distortion from overlapping predictor information here (Hair, Hult, Ringle, & Sarstedt, 2022).

2. **Coefficient of Determination (R^2) and Effect Size (f^2)**

R^2 captures how well all the predictors together explain variation in the dependent variable. F^2, on the other hand, zooms in on each individual predictor's own contribution to that explanatory power. In short, R^2 speaks to the model as a whole, while f^2 breaks it down predictor by predictor.

Table 6. Coefficient of Determination (R^2) and Predictive Accuracy

Endogenous Construct	R^2	Adjusted R^2	Category
Behavioral Intention (BI)	0.612	0.605	Moderate–strong
Use Behavior (UB)	0.687	0.681	Strong

Source: SEM PLS Output, 2026

Table 6 shows the model explaining 61.2 percent of the variance in Behavioral Intention, and 68.7 percent in Use Behavior. Both figures land in the moderate-to-strong range under Chin's (1998) guidelines. Together, UTAUT2's determinants and Policy Trust clearly carry enough explanatory weight to account for mobile money adoption behavior.

Table 7. Effect Size (f^2) of Structural Paths

Path	f^2	Category
PE → BI	0.086	Small
EE → BI	0.052	Small
SI → BI	0.038	Small
HM → BI	0.061	Small
PV → BI	0.104	Small–medium
HT → BI	0.142	Medium
PT → BI	0.178	Medium
FC → UB	0.095	Small
HT → UB	0.156	Medium
BI → UB	0.298	Small–medium

Source: SEM PLS Output, 2026

Table 7 reveals real variation in how much each predictor contributes. Behavioral Intention's effect on Use Behavior stands out as the strongest (0.298). Policy Trust's effect on BI comes next at 0.178—and notably, that outpaces several conventional UTAUT2 determinants, including Social Influence (0.038) and Hedonic Motivation (0.061). This pattern says something worth noting: trust in government policy carries a fairly substantial weight in shaping usage intention, comparable even to a core determinant like Habit (0.142).

3. **Predictive Relevance (Q^2) and Model Fit**

Q^2 assesses the model's predictive capability through the blindfolding procedure. SRMR, meanwhile, checks how well the model fits the empirical data overall. A positive Q^2 signals predictive relevance. A low SRMR points to good model fit.

Table 8. Predictive Relevance (Q^2) and Model Fit Indices

Endogenous Construct	Q^2 (Blindfolding)	Category
Behavioral Intention (BI)	0.398	Medium–strong predictive relevance
Use Behavior (UB)	0.452	Medium–strong predictive relevance
Fit Index	**Value**	**Threshold**
SRMR	0.061	< 0.08

Source: SEM PLS Output, 2026

Table 8 shows Q^2 values above zero and an SRMR of 0.061—well within the 0.08 threshold. Together, these confirm the model has both predictive relevance and good fit with the empirical data (Hair et al., 2022; Henseler et al., 2016). The model is now ready for hypothesis testing through bootstrapping.

Hypothesis Testing (Bootstrapping)

Hypothesis testing relied on bootstrapping with 5,000 subsamples, generating t-statistics and p-values at the 5 percent significance level ($t \geq 1.96$ or $p < 0.05$). These figures determine whether each research hypothesis holds up empirically.

1. **Testing the Direct Effect Hypotheses (H_1–H_{10})**

Table 9. Path Coefficients and Hypothesis Testing Results (Direct Effects)

Hypothesis	Path	Original Sample (O)	Sample Mean (M)	Std. Deviation	t-statistic	p-value	Decision

H_1	PE → BI	0.187	0.184	0.055	3.412	0.001	Supported
H_2	EE → BI	0.142	0.139	0.053	2.687	0.007	Supported
H_3	SI → BI	0.071	0.069	0.055	1.284	0.199	Not Supported
H_4	HM → BI	0.156	0.153	0.053	2.945	0.003	Supported
H_5	PV → BI	0.198	0.196	0.051	3.876	0.000	Supported
H_6	HT → BI	0.221	0.218	0.053	4.203	0.000	Supported
H_7	FC → UB	0.176	0.174	0.056	3.124	0.002	Supported
H_8	HT → UB	0.203	0.201	0.055	3.687	0.000	Supported
H_9	BI → UB	0.312	0.309	0.053	5.892	0.000	Supported
H_{10}	PT → BI	0.234	0.231	0.052	4.512	0.000	Supported

Source: SEM PLS Output, 2026

Table 9 shows 9 out of 10 direct-effect hypotheses receiving support. The exception is H_3—Social Influence's effect on Behavioral Intention turned out not significant. Policy Trust, meanwhile, emerges as one of the strongest predictors of Behavioral Intention ($\beta = 0.234$; $p < 0.001$), even outpacing several UTAUT2 constructs. The strongest coefficient of all, though, belongs to Behavioral Intention's effect on Use Behavior ($\beta = 0.312$). Usage intention, it turns out, remains the primary driver of what people actually do.

2. **Testing the Moderation Effect Hypotheses (H_{11}–H_{12})**

Table 10. Moderating Effect Testing Results (Two-Stage Approach)

Hypothesis	Interaction Term	Original Sample (O)	Std. Deviation	t-statistic	p-value	Decision
H_{11}	PT × PV → BI	0.128	0.055	2.341	0.019	Supported
H_{12}	PT × FC → UB	0.109	0.052	2.087	0.037	Supported

Source: SEM PLS Output, 2026

Table 10 confirms both of Policy Trust's moderating effects reached significance. It strengthens the effect of Price Value on Behavioral Intention ($\beta = 0.128$; $p = 0.019$), and it does the same for Facilitating Conditions on Use Behavior ($\beta = 0.109$; $p = 0.037$). Policy Trust, then, isn't just a direct predictor. It amplifies how the core UTAUT2 determinants drive mobile money adoption.

Of the 12 hypotheses tested, 11 found support, and just one didn't—a 91.7 percent support rate overall. That's a fairly strong showing. But the one hypothesis that didn't hold up deserves attention too. It's not just a statistical footnote; it's a finding worth unpacking on its own theoretical terms.

DISCUSION

Taken as a whole, the findings suggest something UTAUT2 alone can't fully capture: rational determinants no longer tell the complete story of how Ghanaian MSMEs adopted mobile money after the E-Levy's repeal (Venkatesh, Thong, & Xu, 2012). Performance expectancy and effort expectancy still matter, consistent with Penney et al. (2021), but their influence gets overshadowed by policy trust. That's a telling result. It suggests confidence in the government's policy consistency has become a primary consideration in mobile money use—echoing Baah-Peprah et al.'s (2024) argument about the importance of government trust in electronic taxation contexts.

Social influence, on the other hand, showed no significant effect—a departure from what Alalwan et al. (2017) found. This points to something worth considering: in the aftermath of a policy shock, institutional credibility may simply carry more weight than social pressure does.

This study's findings close gaps on four fronts. Theoretically, policy trust's significance as both predictor and moderator makes a strong case for extending UTAUT2 through policy feedback theory (Pierson, 1993). Empirically, these results help explain why earlier research on trust and facilitating conditions produced such mixed signals, including the diverging findings of Alalwan et al. (2017) and Kwateng et al. (2018).

Contextually, this study offers early evidence from Ghanaian MSMEs in the post-E-Levy repeal period, moving beyond where Mensah et al. (2022) left off. Methodologically, the two-stage approach captured policy trust's moderating effects in ways previous research—including Dodoo et al. (2025)—hadn't managed to explain. Put together, this isn't just a new construct bolted onto UTAUT2. It's a fresh way of thinking about financial technology adoption when the policy landscape refuses to sit still.

The Conventional UTAUT2 Determinants of Behavioral Intention

H_1's findings show performance expectancy significantly shaping behavioral intention, consistent with Penney et al. (2021) and UTAUT2's core premise (Venkatesh, Thong, & Xu, 2012). Effort expectancy (H_2) proved significant too, aligning with Krah et al. (2024)—though its effect was smaller than performance expectancy's. Something specific seems to be happening among Ghanaian MSME operators here. They appear to weigh the practical benefits of mobile money more heavily than how easy it is to use, a pattern that echoes Baptista and Oliveira's (2015) findings.

H_3's results show social influence carrying no significant weight on behavioral intention, a finding that departs from Alalwan et al. (2017). Something's shifted in the post-E-Levy repeal period. Adoption decisions now seem driven more by trust in institutional credibility than by social pressure, a pattern that aligns with Tian and Chan (2024).

Hedonic motivation (H_4) tells a different story. It came through as significant, reinforcing what Alalwan et al. (2018) found—that the experience of using mobile money still matters a great deal to MSME operators making adoption decisions.

Price value (H_5) came through as significant for behavioral intention, matching what Takyi (2024) and Venkatesh et al. (2012) found. Cost perception, it seems, still weighs heavily on mobile money adoption even after the E-Levy's repeal. Habit (H_6), meanwhile, posted the largest coefficient among all UTAUT2 determinants—consistent with Dodoo et al. (2025). Mobile money use, in other words, has settled deep into the daily routines of Ghanaian MSMEs.

Taken together, H_1 through H_6 show most UTAUT2 determinants holding up well among Ghanaian MSMEs in the post-E-Levy repeal period—social influence being the lone exception. Perhaps that's telling. Social influence's role here may be better explained through the dynamics of policy trust than through conventional UTAUT2 alone.

Direct Path to Use Behavior

Facilitating conditions showed a significant effect on use behavior (H_7), aligning with Alalwan et al. (2017) but diverging from Kwateng et al. (2018). That divergence isn't random. As H_{12} demonstrates, the strength of facilitating conditions' influence actually depends on the level of policy trust in play. In other words, this relationship isn't fixed—and previous models that left out the policy trust dimension simply couldn't have captured that.

Habit significantly influenced use behavior (H_8), consistent with Dodoo et al. (2025). Its consistent effect across both behavioral intention (H_6) and use behavior (H_8) lends further support to UTAUT2's core premise (Venkatesh, Thong, & Xu, 2012)—that habit shapes intention and actual behavior alike. This says something notable about Ghanaian MSMEs. Their mobile money use has settled into a fairly stable routine, one that held steady even through major policy upheaval.

Behavioral intention emerged as the strongest predictor of use behavior (H_9), consistent with UTAUT2 (Venkatesh et al., 2012) and Penney et al.'s (2021) findings. Intention, it turns out, still holds the top spot in explaining mobile money use—even with policy trust and other contextual factors pulling at the edges.

Looking at H_7 through H_9 as a group, direct paths to use behavior still run largely through conventional UTAUT2 mechanisms. But there's a catch. The strength of one path in particular—facilitating conditions—can't be fully understood without factoring in policy trust's moderating role. That role, it turns out, is exactly what explains why earlier FC findings in the literature never quite lined up.

The Role of Policy Trust as a New Construct

Policy trust showed a positive, significant effect on behavioral intention—one that outweighed even performance expectancy and effort expectancy. This confirms something important: mobile money adoption after a policy shock isn't driven by benefits and ease of use alone. Trust in government policy matters too, echoing Baah-Peprah et al. (2024). When tested within a single model, policy trust's influence even surpassed several of UTAUT2's core determinants.

Policy trust's outsized influence suggests MSME operators judge the government on more than just competence. Good faith and integrity in policymaking matter too (Mayer et al., 1995). This finding also lends weight to policy feedback theory (Pierson, 1993)—the idea that a policy's effects can linger in behavior long after the policy itself is gone. The E-Levy's repeal removed the financial burden, sure. But it didn't fully erase the residue of distrust still shaping how people decide to adopt mobile money.

This finding reinforces what Mensah, Mwakapesa, Mensah, and Mensah (2022) already suspected—conventional UTAUT simply couldn't explain how the E-Levy affected sustained mobile money use. This study, though, goes a step further. It formulates policy trust as a construct that's not only significant but empirically distinct from the generic trust Dodoo, Xin, Mangudhla, Boadi, Dimen, and Nuta (2025) tested, a distinction the low HTMT values make clear.

Something broader emerges from this. UTAUT2 needs room to grow when applied to contexts shaken by policy turbulence. Policy trust offers exactly that room—accommodating these conditions without disturbing the model's basic structure.

The Moderating Effect of Policy Trust

Policy trust turned out to moderate the relationship between price value and behavioral intention (H_{11}: $\beta = 0.128$; $t = 2.341$; $p = 0.019$). What this means, practically, is that perceived cost savings after the E-Levy's repeal only translate into stronger usage intention when MSME operators actually believe the repeal is here to stay. At lower levels of policy trust, though, those same cost benefits carry less weight—lingering worry that a similar levy might return tends to dampen their effect. This adds something to Takyi's (2024) work. Behind the post-repeal transaction surge, it seems, the link between price value and usage intention hinges on how much trust individuals place in the policy itself.

Policy trust also moderated the link between facilitating conditions and use behavior (H_{12}: $\beta = 0.109$; $t = 2.087$; $p = 0.037$). This helps explain a puzzle in the literature—why Alalwan, Dwivedi, and Rana (2017) and Kwateng, Atiemo, and Appiah (2018) arrived at such different conclusions. Infrastructure availability, whether agents, network access, or technical support, only translates into actual use when MSME operators trust the government to keep its policy commitments steady. Policy trust, in effect, works as a catalyst here. It's what turns infrastructure support into real usage behavior, echoing Levi and Stoker's (2000) concept of institutional trust.

Both moderating effects point to the same conclusion: price value and facilitating conditions don't carry a fixed influence within UTAUT2. Their strength shifts depending on the level of policy trust at play. This offers a new lens on why earlier studies produced such inconsistent results. Cultural or sample differences might not be the whole story—variation in policy trust, left unmeasured in prior work, could be quietly driving those discrepancies too.

Theoretical Discussion

This finding pushes back against one of UTAUT2's core assumptions—that the policy environment is a stable, external factor (Venkatesh, Thong, & Xu, 2012). Policy trust's significance, both as predictor and moderator, tells a different story. In developing countries where digital fiscal policy can shift without warning, the institutional environment isn't passive background noise. It actively shapes whether UTAUT2's determinants ever translate into real intention and behavior. That's the real contribution here. This study doesn't just tack on a new construct. It stretches UTAUT2's foundational assumptions to make room for policy trust.

This study speaks directly to a long-standing critique of UTAUT2—that it fits developed-country contexts better, where policy stays relatively stable, and loses explanatory power in developing countries facing regulatory volatility (Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2019). The findings here suggest UTAUT2 remains largely relevant (H_1, H_2, H_4, H5, H_6). But it needs extending, particularly through policy trust, and particularly along two paths: price value and facilitating conditions, the two most exposed to government intervention.

The logic makes sense once you look closer. Price value ties directly to the cost structures tax policy creates. Facilitating conditions, meanwhile, depend on how digital infrastructure gets regulated. So this isn't just another paper claiming trust matters in developing countries. It shows, with some precision, exactly how policy trust moderates these two specific paths in explaining mobile money adoption.

At a broader level, this study bridges two traditions that have long run on separate tracks—technology acceptance research (Venkatesh et al., 2012) and policy feedback theory (Pierson, 1993). The findings suggest something worth sitting with: technology users are also policy subjects. Adoption decisions, it turns out, aren't purely rational calculations. They're shaped by lived experience with government policy too.

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Policy trust is what ties these two perspectives together in a single model. And that opens a door. Future research now has room to look at fintech users in developing countries as more than just rational actors weighing costs and benefits—as people navigating policy history as well.

That said, this extension doesn't replace UTAUT2—it refines it. Habit and behavioral intention still exert strong effects on use behavior (H_8, H_9), confirming the model's core mechanisms hold up just fine. What needed revisiting was a different assumption: that these determinants operate independently of institutional context. They don't. And that's precisely the point—this study refines UTAUT2's basic premise rather than tearing it down.

CONCLUSION

This study set out to test an extension of UTAUT2 through the construct of policy trust, aiming to explain how Ghanaian MSMEs adopted mobile money after the E-Levy's repeal. The results answer that original question convincingly. Trust in government policy isn't a supplementary variable tacked onto the model—it's a central mechanism that determines how effectively conventional technology acceptance determinants actually work. Of the 12 hypotheses tested, 11 found empirical support. Policy trust played a double role throughout: as a direct predictor of usage intention, one whose strength outpaced most core UTAUT2 determinants, and as a moderator shaping whether price value and facilitating conditions ever translated into real intention and behavior. Only one hypothesis failed to hold—social influence's effect on behavioral intention—and even that reinforces the study's central argument. In the aftermath of policy shock, adoption decisions seem to shift away from social-normative reasoning and toward individual calculations about institutional credibility.

These findings make one thing clear: UTAUT2 in its original form falls short in developing countries exposed to digital fiscal policy turbulence, largely because the model quietly assumes a stable, neutral institutional environment. By weaving policy feedback theory into UTAUT2's architecture, this study shows something the original model couldn't capture—the trust residue left behind by a policy's rise, resistance, and repeal doesn't simply vanish once transaction costs disappear. It lingers, continuing to shape adoption calculations well into the future. This is a refinement, not a replacement, of UTAUT2's basic premise. Its core determinants remain largely relevant, but their explanatory power now appears conditional on the surrounding climate of institutional trust—a nuance mainstream technology acceptance research, and earlier UTAUT2 studies in Ghana, never treated as an explicit contextual variable.

Taken together, this research closes the theoretical, empirical, contextual, and methodological gaps mapped out back in the Introduction. It also offers something new for financial technology adoption research in developing countries going forward. Technology users, it turns out, can't be understood purely as rational consumers weighing costs and benefits. They're policy subjects too, carrying their institutional experiences into every adoption decision they make.

LIMITATION

This study comes with its share of limitations. The cross-sectional design captures respondent perceptions at just one point in time, which means it can't really speak to how policy trust shifts and evolves. Self-report data brings its own risk too—common method bias is always a concern, and real transaction data would have strengthened how use behavior gets measured.

There's a sampling limitation as well. The study only covered MSMEs in Accra, Kumasi, and Sekondi-Takoradi, so generalizing these findings to rural areas calls for caution. Policy trust itself is still a new construct, one that needs further validation across different contexts. And focusing specifically on Ghana's E-Levy case limits how far these findings can travel to countries with different digital policy landscapes.

Future research could address several of these gaps. A longitudinal design would help. So would extending the analysis to other countries, and pairing survey data with actual transaction records.

REFERENCES

Alalwan, A. A., Baabdullah, A. M., Rana, N. P., Tamilmani, K., & Dwivedi, Y. K. (2018). Examining adoption of mobile internet banking: A cross-cultural study of Jordan and the United Kingdom. *Technology in Society, 55*, 100–110. https://doi.org/10.1016/j.techsoc.2018.06.007

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management, 37*(3), 99–110. https://doi.org/10.1016/j.ijinfomgt.2017.01.002

Baah-Peprah, P., Nyarko, S., Flåten, B., Naatu, F., & Serwaah, P. (2024). Trust in government, electronic taxation, and the adoption of fintech. *Journal of Alternative Finance, 1*(3), 213–235. https://doi.org/10.1177/27533743241286156

Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior, 50*, 418–430. https://doi.org/10.1016/j.chb.2015.04.024

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–336). Lawrence Erlbaum Associates.

Dodoo, R. N. A., Xin, F., Mangudhla, T., Boadi, E. B., Dimen, L., & Nuta, A. C. (2025). The paradox of mobile money adoption among Ghana's petty traders: A two-stage PLS-SEM-ANN approach. *SAGE Open, 15*(4). https://doi.org/10.1177/21582440251378112

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers, 21*(3), 719–734. https://doi.org/10.1007/s10796-017-9774-y

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications.

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management & Data Systems, 116*(1), 2–20. https://doi.org/10.1108/IMDS-09-2015-0382

Krah, R., Tetteh, L. A., Boateng, A., & Amankwa, R. F. (2024). Financial technology adoption among small and medium enterprises in Ghana. *Cogent Business & Management, 11*(1), Article 2321786. https://doi.org/10.1080/23311975.2024.2321786

Kwateng, K. O., Atiemo, K. A. O., & Appiah, C. (2018). Acceptance and use of mobile banking: An application of UTAUT2. *Journal of Enterprise Information Management, 32*(1), 118–151. https://doi.org/10.1108/JEIM-03-2018-0055

Levi, M., & Stoker, L. (2000). Political trust and trustworthiness. *Annual Review of Political Science, 3*, 475–507. https://doi.org/10.1146/annurev.polisci.3.1.475

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review, 20*(3), 709–734. https://doi.org/10.2307/258792

Mensah, I. K., Mwakapesa, D. S., Mensah, P. A., & Mensah, J. K. (2022). The impact of government electronic transaction levy on the continuous adoption of mobile money transactions in Ghana. *Proceedings of the 4th Africa-Asia Dialogue Network (AADN) International Conference on Advances in Business Management and Electronic Commerce Research*. ACM. https://doi.org/10.1145/3572996.3573001

Penney, E. K., Agyei, J., Boadi, E. K., Abrokwah, E., & Ofori-Boafo, R. (2021). Understanding factors that influence consumer intention to use mobile money services: An application of UTAUT2 with perceived risk and trust. *SAGE Open, 11*(3). https://doi.org/10.1177/21582440211023188

Pierson, P. (1993). When effect becomes cause: Policy feedback and political change. *World Politics, 45*(4), 595–628. https://doi.org/10.2307/2950710

Takyi, P. O. (2024). The impact of electronic levy on mobile money transactions: Lessons from Ghana. *Policy Studies, 46*(2), 271–287. https://doi.org/10.1080/01442872.2024.2303348

Tian, Y., & Chan, T. J. (2024). Predictors of mobile payment use applications from the extended technology acceptance model: Does self-efficacy and trust matter? *SAGE Open, 14*(4). https://doi.org/10.1177/21582440241292525

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157–178. https://doi.org/10.2307/41410412