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When acceptance doesn't convert: The mobile acceptance–purchase gap in health-device mCommerce: Evidence from home blood pressure monitors in Lagos, Nigeria

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Abstract

Technology acceptance models assume that favourable evaluations of a digital channel led to its use and, ultimately, to purchase. This study tests that assumption in a high-involvement, health-related category: home blood pressure monitoring (HBPM) devices in Lagos, Nigeria. Drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT) and the intention–behaviour literature, it examines whether mobile shopping acceptance predicts four stages of consumer purchase (product awareness, brand perception, purchase intention and actual purchase behaviour) and whether age and hypertension diagnosis status condition these relationships. Survey data from 231 HBPM consumers recruited across pharmacy, hospital, online and medical-representative channels were analysed with partial least squares structural equation modelling (PLS-SEM), 5,000-subsample bootstrapping, PLSpredict and permutation-based multigroup analysis. Mobile shopping acceptance was high (67–71% agreement on every item), but it had no significant effect on any purchase stage (all $|\beta| \leq 0.109$, all $p \geq 0.256$, $R^2 \leq 0.012$), and all Q^2predict values were negative. Purchase intention did not predict actual purchase behaviour. Consumers who accepted mobile shopping were no more likely to report completed purchases than those who did not (43.2% vs 40.8%; $\chi^2 = 0.06$, $p = 0.812$). Multigroup comparisons by age (<45 vs ≥45) and diagnosis status revealed no significant differences. Bootstrap confidence intervals rule out moderate or large effects. The findings identify a boundary condition for UTAUT in health-device mCommerce: in a market where 73.6% of purchases occur in pharmacies, mobile acceptance functions as a channel attitude rather than a purchase driver. It is recommended that HBPM retailers and digital pharmacies build pharmacist consultation, product-authenticity verification and links to trusted pharmacies into their mobile platforms rather than rely on mobile acceptance to drive sales, and that future research test trust, perceived risk and task–technology fit as mediators of the gap.

Keywords: mobile shopping, UTAUT, intention–behaviour gap, home blood pressure monitoring, health-device retailing, Nigeria, PLS-SEM.

1. Introduction

Hypertension is among the leading contributors to the global burden of cardiovascular disease, and its prevalence continues to rise fastest in low- and middle-income countries (Mills et al., 2020). In Nigeria, a systematic analysis estimated that roughly a third of adults are hypertensive, while awareness, treatment and control remain low (Adeloye et al., 2021). Home blood pressure monitoring (HBPM) devices extend detection and self-management beyond the clinic, and digital

self-management tools are increasingly used by Nigerian patients (Dozie et al., 2025). Yet uptake of home monitoring remains uneven, constrained by awareness, cost and concerns about product authenticity (Shedul et al., 2022; Umuerri et al., 2023). How these devices reach consumers is therefore a public health question as much as a retail one.

Smartphones, mobile money and e-commerce platforms have completely revolutionised the retail environment in Nigeria. Mobile shopping – search, compare, pay, remind – it is generally believed that mobile shopping cuts the cost of acquiring the health products. This optimism is confirmed by technology acceptance theory. The Unified Theory of Acceptance and Use of Technology (UTAUT) posits that performance expectancy, effort expectancy and facilitating conditions influence intention and intention further impacts use (Venkatesh et al., 2003; Venkatesh et al., 2012). Evidence shows that these beliefs of acceptance account for consumer adoption of electronic payments and mobile health applications in Nigeria (Adanigbo et al., 2025; Foluke et al., 2025).

Acceptance, however, is not purchase. A large body of work shows that intentions translate into behaviour only partially (Sheeran, 2002; Sheeran & Webb, 2016), and meta-analytic evidence on UTAUT shows that many of its relationships are weaker and more context-dependent than the original model implies (Blut et al., 2022). The transition from accepting a channel to purchasing a product through it can be a delicate one, especially for health devices - so consumers need to trust the device is genuine and clinically accurate; and, in certain markets, pharmacists play an important role in providing consumers with that trust (Nelissen et al., 2018; Shedul et al., 2022).

The problem this study addresses lies in the link between these variables. Mobile shopping acceptance, the independent variable, is widely assumed to move consumers through the stages of purchase: awareness of the product category, perception of its brands, intention to buy and, finally, the purchase itself. In Nigeria's HBPM market, however, purchase is anchored in pharmacies, where trust and clinical assurance are supplied in person (Nelissen et al., 2018; Shedul et al., 2022). Whether mobile acceptance translates into awareness, brand perception, intention and completed purchase therefore remains unproven. The same is true of whether intention converts into purchase, and of whether these relationships differ by age (older consumers are expected to face greater digital barriers) and by hypertension diagnosis (diagnosed consumers have a clinical need but also rely on clinicians and pharmacists). Without this evidence, retailers and digital pharmacies risk investing in mobile channels on the strength of favourable attitudes alone, and acceptance models risk overstating what acceptance explains in health-device markets.

This study fills the gap using a sample of 231 HBPM consumers in Lagos. The study has three contributions. First, it offers the first measure of the relationship between mobile acceptance and purchase in the Nigerian market for health devices with a "staged" in between. Secondly, reporting with confidence intervals, out-of-sample prediction tests and multigroup tests puts on record that not finding an effect is not just a matter of statistical power. Third, it is a boundary that is identified for UTAUT: where purchase is rooted in a trusted physical channel, high acceptance of a digital channel does not affect purchases measurable.

The objectives of the study are therefore to:

(i) examine the effect of mobile shopping acceptance on product awareness, brand perception, purchase

intention and actual purchase behaviour among HBPM consumers in Lagos;
(ii) determine whether purchase intention predicts actual purchase behaviour;
(iii) assess whether the effects of mobile shopping acceptance on purchase outcomes differ between consumers aged under 45 and those aged 45 and above; and
(iv) assess whether these effects differ between consumers with and without a hypertension diagnosis.

2. Literature Review

2.1 Mobile shopping and technology acceptance

Mobile shopping is the interaction with mobile devices and apps throughout the shopping process – from the initial information search and comparison to purchase and follow-up reminders. UTAUT builds on previous acceptance models such as the Technology Acceptance Model (Davis, 1989) into four factors that influence intention and use: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). UTAUT2 is an extension of the model to consumer context that introduces hedonic motivation and price value and habit (Venkatesh et al., 2012). In this study, mobile shopping acceptance consists of consumers' attitudes toward performance expectancy and effort expectancy of different mobile tools utilized for HBPM search, payment, health tracking, and reminder respectively.

The study's predictions are supported by a number of empirical studies in Nigeria, with one arguing that acceptance beliefs lead to the adoption of digital payment (Adanigbo et al., 2025) and another that acceptance beliefs have a similar predictive power for the usage of mobile health apps (Foluke et al., 2025). Research among older people indicates that perceived usefulness, ease of use and facilitating conditions are also influential factors in mHealth adoption, whereas technology anxiety and resistance to change are deterrent factors (Hoque & Sorwar, 2017). Nevertheless, a systematic review of UTAUT studies revealed that some of the central relationships of the model were more variable and smaller in different contexts than presented in the original model (Blut et al., 2022), making it important to consider boundary conditions.

2.2 Consumer purchase as a staged process

Hierarchy-of-effects models describe purchase as a sequence of cognitive, affective and conative stages (Lavidge & Steiner, 1961). Following this logic, consumer purchase is treated here as four related outcomes: product awareness, brand perception, purchase intention and actual purchase behaviour. Omnichannel research shows that consumers combine channels across these stages, for instance researching online and buying offline (Verhoef et al., 2007), and that channel effects therefore differ by stage (Verhoef et al., 2015). A stage-specific design can reveal whether a channel works upstream, by building awareness and brand perceptions, or downstream, by converting intention into purchase.

2.3 The intention–behaviour gap

The theory of planned behaviour treats intention as the proximal cause of behaviour (Ajzen, 1991). Meta-analyses, however, show that intentions explain on average less than 30% of the variance in behaviour, and that many people with positive intentions fail to act (Sheeran, 2002; Sheeran & Webb, 2016). The gap widens when behaviour requires resources, involves risk, or depends on external conditions. Purchasing a health device online carries performance and financial risk (Featherman & Pavlou, 2003) and requires trust in the seller (Gefen et al., 2003), so positive evaluations of a channel

may not be enough to complete a purchase through it. Task-technology fit theory adds that a technology improves outcomes only when its functions match the task (Goodhue & Thompson, 1995); Nigerian evidence shows that trust and task-technology fit are both needed for e-payment use (Oni et al., 2022).

2.4 HBPM device retail in Nigeria

HBPM devices can be purchased in Nigeria from community pharmacies, hospitals and medical representatives, in addition to online market places. In Lagos, pharmacies are seen as having a significant part in the care of patients with hypertension, also in pilots involving an integration of pharmacies into mHealth (Nelissen et al., 2018). The worry about poor-quality and manipulated cardiovascular products is also ubiquitous, compelling consumers to go for trusted outlets as the consequence (Shedul et al., 2022). Awareness, cost, and perceived barriers affect self-monitoring practice (Umuerri et al., 2023), and acceptability of mHealth needs to be measured contextually, as done in studies of the acceptability of mHealth in Nigeria (Lynch et al., 2022). The attributes indicate that there might be a lower relationship between the acceptance of mobile and the intention to buy the HBPM than the overall UTAUT evidence suggests.

Hypothesis Development

Consumers who are satisfied with the use of mobile tools will use them more and access more product info, according to UTAUT. The consumer should see the product categories and brands through mobile search and comparison which should help him to raise awareness of a product.

H1. Mobile shopping acceptance positively affects product awareness.

Mobile platforms display reviews, ratings and a consistent message. Users of them must be able to develop more positive and distinct brand perceptions as the more they use them, the more positive and distinct these perceptions will be.

H2. Mobile shopping acceptance positively affects brand perception.

Venkatesh et al. (2003) and Venkatesh et al. (2012) identified the two key factors that affect behavioural intention: performance and effort expectancy in UTAUT. Customers who consider mobile shopping easy and effective are likely to be more willing to purchase a mobile device if this is applied to HBPM.

H3. Mobile shopping acceptance positively affects purchase intention.

Also, UTAUT sees facilitating conditions and acceptance as linked to actual use. Faster and easier discovery, payment and reordering on mobile should boost the number of purchases completed.

H4. Mobile shopping acceptance positively affects actual purchase behaviour.

In both UTAUT and the theory of planned behaviour (Ajzen, 1991) the proximal antecedent of behaviour is intention, though the relationship is not necessarily strong (Sheeran, 2002).

H5. Purchase intention positively affects actual purchase behaviour.

There are some UTAUT relationships that are moderated by age: older consumers are more likely to have to make a greater effort to buy digitally and to consider effort and facilitating conditions more strongly, and are more likely to have greater barriers to digital purchase (Venkatesh et al., 2003; Hoque & Sorwar, 2017). Mobile acceptance to intention to buy and to actually make the purchase might be lower among older consumers in the HBPM market as most of the people involved in the market are in the middle age and above.

H6. The effects of mobile shopping acceptance on purchase outcomes differ between consumers aged under 45 and those aged 45 and above.

People with a diagnosis of hypertension have a clinical need to be monitored and

are more likely to be receptive to positive channel assessments when purchasing medication when compared to the purchase for prevention. On the other hand, diagnosed consumers might listen more to a clinicians and pharmacists.

H7. The effects of mobile shopping acceptance on purchase outcomes differ between consumers with and without a hypertension diagnosis.

Conceptual Framework

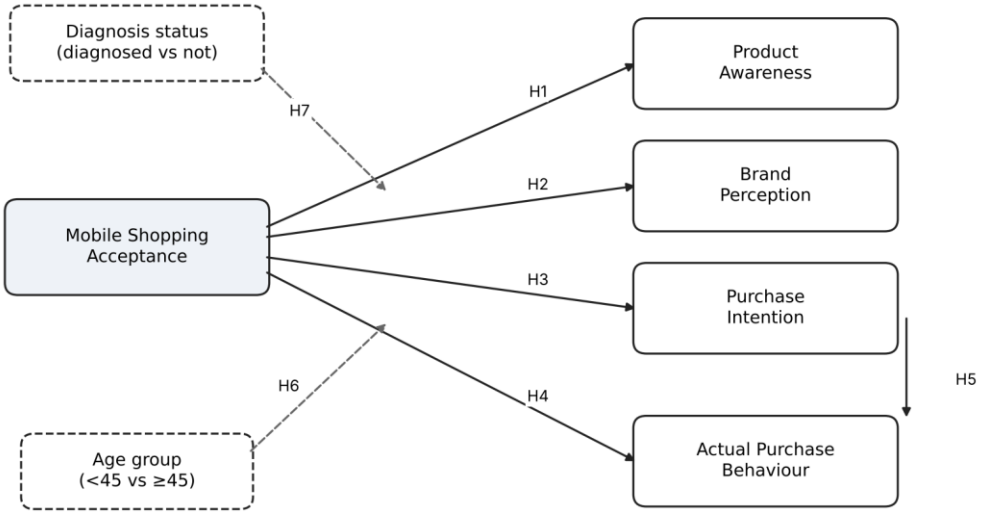


Figure 1. Research framework

3. Methodology

3.1 Research design and population of the study

The study adopted a quantitative, cross-sectional survey design. The study population comprised adult consumers (aged 18 and above) who had purchased HBPM devices in Lagos State through any of four retail channels: community and retail pharmacies (Lagos Island and Lagos Mainland); outpatient and chronic-disease clinics in public and private hospitals; online health retail outlets; and medical representatives involved in community outreach. The accessible population across the four channels was 385 consumers.

3.2 Sample size and sampling technique

The sample size was determined with the Taro Yamane (1967) formula for finite populations, $n = N / [1 + N(e^2)]$, where N is the population (385) and e is the margin of error (0.05, at the 95% confidence level). This gave a minimum sample of 196 respondents ($n = 385 / [1 + 385 \times 0.0025] \approx 196$). To allow for non-response and for incomplete or invalid questionnaires, and to meet the sample requirements of PLS-SEM (Hair et al., 2019), 247 questionnaires were administered across the four channels, allocated in proportion to each channel's share of the accessible population. Of these, 231 were validly completed and returned, a usable response rate of 93.5%, which exceeds both the Yamane minimum and the PLS-SEM threshold.

A purposive (non-probability) sampling technique was used so that only respondents with direct experience of HBPM devices and their purchase channels were included. The sampling frame was compiled, with the cooperation of participating retail and healthcare institutions, from pharmacy customer records, hospital outpatient purchase logs, online platform transaction data and medical representatives' contact lists, and

was checked to remove duplicate entries. Respondents were eligible if they were aged 18 or above and had purchased an HBPM device through at least one of the four channels in Lagos State within the six months before data collection, or were actively evaluating such a purchase at the time of the survey. Ethics approval reference and consent procedure is to be included in authors' manuscript.

3.3 Measures and data analysis

The scoring of all constructs was done on a 5-point likert scale where the extreme options were E. 5 = strongly agree.E. = Strongly disagree, 1 = Strongly agree. The following questions were adapted for the HBPM context: Are there essential elements or factors that are omitted to make it a perfect HBPM? (strongly agree = 5) The mobile shopping acceptance constructs; Mobile Search and comparison, Mobile shopping comfort with payment, BP tracking apps driver of mobile shopping motivation, BP tracking apps reminder to reorder, and ease with mobile shopping purchase process, are included in the mobile shopping acceptance constructs. Product awareness (PA1 – PA4), brand perception (BP1 – BP4), purchase intention (PI1 – PI4) and actual purchase behaviour (APB1 – APB4) were the four purchase stages identified. Demographic data did a survey of age, gender, educational level, diagnosis of hypertension, home monitoring methods, and the first place and source information on HBPM was obtained. Details of the text of the item are in Appendix A.

Data were analysed with PLS-SEM, which suits prediction-oriented models with composite constructs and non-normal Likert data (Hair et al., 2019). The model was estimated with the Mode A PLS algorithm and path weighting scheme (Lohmöller, 1989), with five reflective constructs and five structural paths (H1–H5) estimated simultaneously. Significance was assessed with 5,000 bootstrap subsamples (percentile 95% confidence intervals). Out-of-sample predictive relevance was assessed with PLSpredict using ten folds and ten repetitions (Shmueli et al., 2019). H6 and H7 were tested with permutation-based multigroup analysis (1,000 permutations), which compares path coefficients between groups without distributional assumptions (Henseler et al., 2016). Common method bias was assessed with Harman's single-factor test and full collinearity variance inflation factors (Podsakoff et al., 2003; Kock, 2015). Finally, to describe the acceptance–purchase gap directly, respondents were classified as acceptors (mean MS score ≥ 4) or non-acceptors and as converters (mean APB score ≥ 4) or non-converters, and the two classifications were cross-tabulated. The original analysis was run in SmartPLS 4 (Ringle et al., 2024); the integrated model reported here was re-estimated to test all paths simultaneously.

4. Results and Discussion

Respondents' characteristics

The respondents were categorised by age, gender, education, diagnosis status, home-monitoring practice, purchase channel and first source of HBPM information (Table 1). Demographic data were missing for one respondent.

Table 1. Respondents' characteristics (N = 231)

Respondents' characteristics	Frequency	Percentage (%)
Age		
Under 25	2	0.9
25–34	31	13.4
35–44	56	24.2

Respondents' characteristics	Frequency	Percentage (%)
45–54	46	19.9
55–64	58	25.1
65 and above	37	16.0
Gender		
Male	118	51.1
Female	112	48.5
Education		
OND	1	0.4
HND/BSc	127	55.0
Postgraduate	100	43.3
Other	2	0.9
Diagnosed with high blood pressure		
Yes	75	32.5
No	150	64.9
Not sure	5	2.2
Frequency of home BP monitoring		
Regularly	98	42.4
Occasionally	95	41.1
Not at all	37	16.0
Channel of most recent purchase		
Pharmacy	170	73.6
Hospital/clinic	3	1.3
Online	5	2.2
Medical representative	30	13.0
Other	22	9.5
First source of HBPM information		
Pharmacist	177	76.6
Doctor/hospital	23	10.0
Community	13	5.6
Online	6	2.6
Advertisement	6	2.6
Family/friends	5	2.2

Note: percentages are of N = 231; one respondent did not complete the demographic section.

Of the 231 respondents, 61.0% were aged 45 or above, gender was nearly balanced, and 98.3% held a first or postgraduate degree. Only 32.5% reported a hypertension diagnosis, indicating that much HBPM demand is preventive. Purchase was concentrated in pharmacies (73.6%), and online purchase accounted for only 2.2%. Pharmacists were the first source of HBPM information for 76.6% of respondents.

Descriptive statistics: high acceptance

Mobile shopping acceptance was the most positively rated construct among the study's channel measures (Table 2). Between 67.1% and 71.4% of respondents agreed or strongly agreed with each item, and no respondent strongly disagreed with MS1–MS4.

Table 2. Mobile shopping acceptance items

Item	Statement (abridged)	Mean	SD	Agree (%)
MS1	Uses mobile apps to search, compare and review HBPM devices	3.81	0.78	67.1
MS2	Comfortable paying for HBPM devices via mobile platforms	3.84	0.83	67.5
MS3	BP-tracking health apps increase motivation to purchase	3.85	0.81	67.5
MS4	Mobile notifications prompt reorder or repurchase	3.84	0.79	69.3
MS5	Mobile platforms make the purchase process easier and more efficient	3.85	0.81	71.4

Agree (%) = agree + strongly agree. Construct mean = 3.84 (SD = 0.66).

Evaluation of the Outer Model

Reliability was assessed with Cronbach's alpha and composite reliability (CR), and convergent validity with indicator loadings and average variance extracted (AVE) (Table 3). All loadings exceeded 0.70 except PA2 (0.727, retained), and APB2 (0.645), which was retained because CR and AVE for the construct exceeded their thresholds and the item is needed for content validity (Hair et al., 2019). Alpha ranged from 0.866 to 0.898, CR from 0.887 to 0.913, and AVE from 0.664 to 0.725. All indicator variance inflation factors were below 2.3.

Table 3. Validity and reliability test results

Variable	Indicator	Loading	VIF	AVE	CR	Cronbach alpha
Mobile Shopping Acceptance	MS1	0.812	2.040	0.664	0.908	0.874
	MS2	0.843	1.709			
	MS3	0.841	2.065			
	MS4	0.806	2.046			
	MS5	0.770	2.204			
Product Awareness	PA1	0.895	1.745	0.725	0.913	0.898
	PA2	0.727	1.683			
	PA3	0.889	1.661			
	PA4	0.884	1.585			
Brand Perception	BP1	0.804	1.891	0.703	0.904	0.866
	BP2	0.846	1.994			
	BP3	0.897	1.959			
	BP4	0.803	1.949			
Purchase Intention	PI1	0.789	1.642	0.712	0.907	0.895
	PI2	0.751	1.855			

Variable	Indicator	Loading	VIF	AVE	CR	Cronbach alpha
	PI3	0.965	1.663			
	PI4	0.853	1.637			
Actual Purchase Behaviour	APB1	0.936	1.656	0.668	0.887	0.897
	APB2	0.645	1.775			
	APB3	0.891	1.689			
	APB4	0.765	1.597			

Discriminant validity was established with the heterotrait–monotrait ratio (HTMT) and the Fornell–Larcker criterion (Henseler et al., 2015; Fornell & Larcker, 1981). All HTMT values were well below 0.85 (maximum 0.180), and the square root of each construct's AVE exceeded its correlations with every other construct (Table 4). Full collinearity VIFs ranged from 1.008 to 1.063, below the 3.3 threshold (Kock, 2015), and the first unrotated factor in Harman's test explained 17.9% of variance, so common method bias is unlikely to be a concern.

Table 4. Discriminant validity: Fornell–Larcker (diagonal and below) and HTMT (above diagonal)

Construct	MS	PA	BP	PI	APB
Mobile Shopping (MS)	**0.815**	0.083	0.109	0.086	0.073
Product Awareness (PA)	−0.094	**0.852**	0.061	0.180	0.052
Brand Perception (BP)	0.109	0.001	**0.839**	0.120	0.066
Purchase Intention (PI)	0.095	−0.194	−0.105	**0.844**	0.050
Actual Purchase Behaviour (APB)	0.059	0.023	0.037	0.052	**0.817**

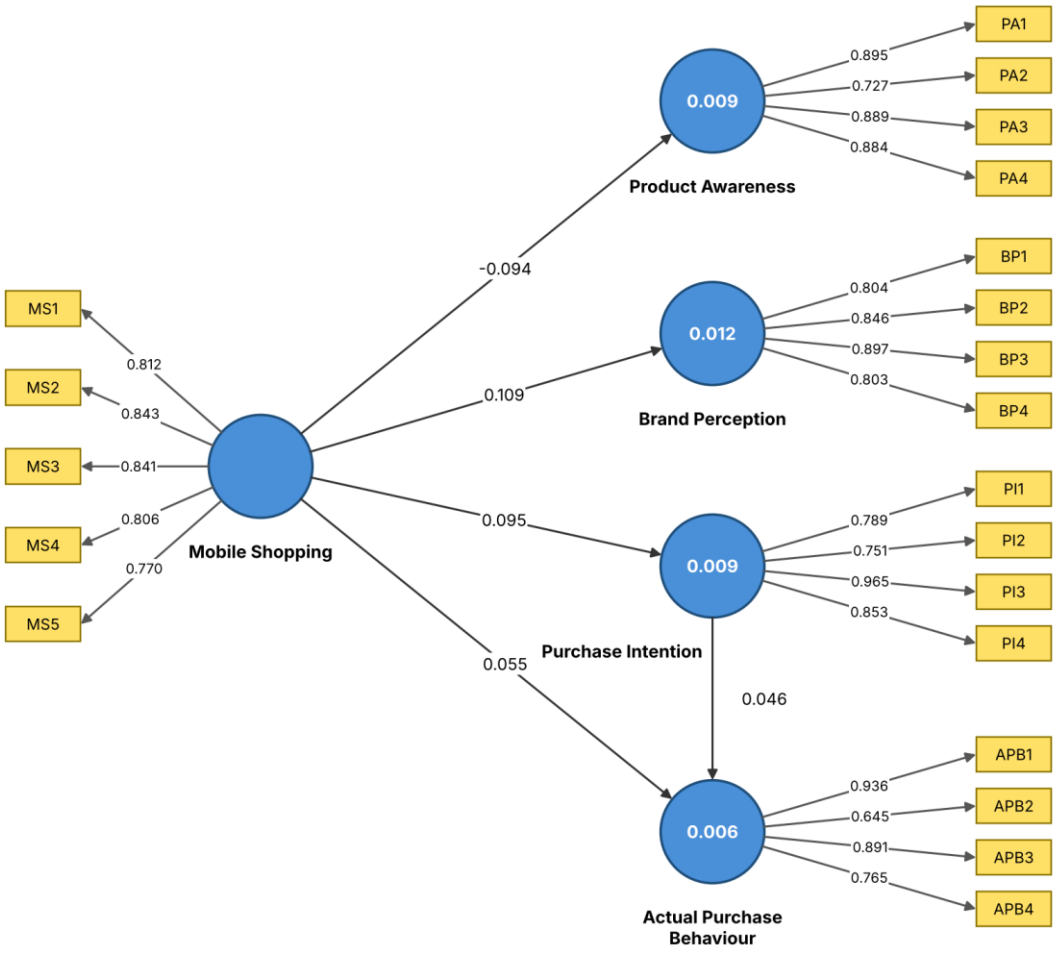
Bold diagonal values are the square roots of AVE.

Inner Model Evaluation

R^2 indicates how much of the variance in each endogenous construct the model explains. As Table 5 shows, mobile shopping acceptance explained around 1% or less of the variance in each purchase stage, and adjusted R^2 values were close to zero. All Q^2predict values were negative, meaning that the model predicted out-of-sample construct scores no better than the training-sample mean (Shmueli et al., 2019).

Table 5. Coefficient of determination and predictive relevance

Variable	R-Square	R-Square adjusted	Q^2predict
Product Awareness	0.009	0.005	−0.002
Brand Perception	0.012	0.008	−0.003
Purchase Intention	0.009	0.005	−0.009
Actual Purchase Behaviour	0.006	−0.003	−0.021

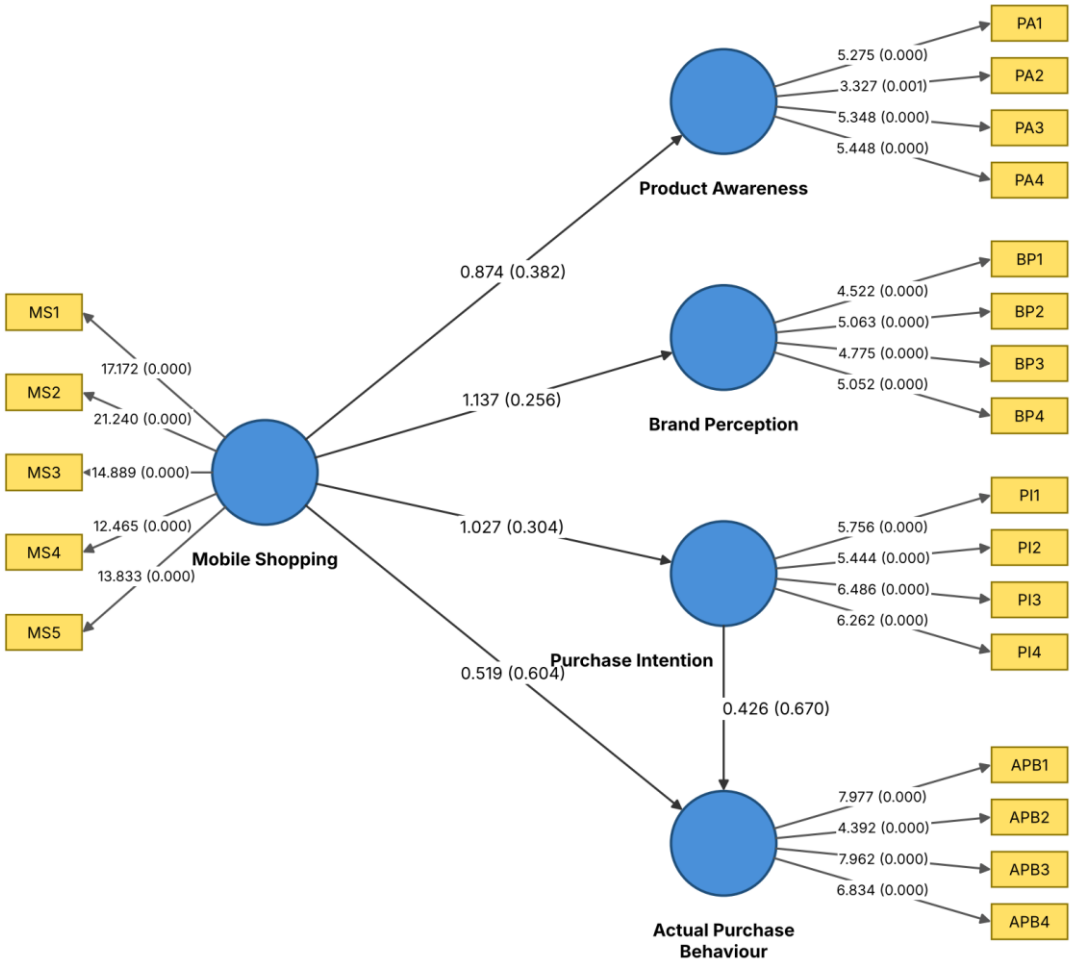


Path coefficients and outer loadings; values inside circles are R^2.

Figure 2. PLS algorithm results: path coefficients, outer loadings and R^2

Path Coefficients

Figure 2 shows the PLS algorithm estimates and Figure 3 the bootstrapping results. All outer loadings were significant (all $t > 3.3$, $p < 0.001$), confirming that each indicator reflects its construct. Path coefficients were evaluated at the 0.05 significance level (Table 6). None of the five structural paths was significant. Every 95% confidence interval included zero, and every upper bound was 0.254 or lower. With N = 231, the study had 80% power at $\alpha = 0.05$ to detect a path coefficient of about 0.16, so the results rule out moderate or large effects rather than merely failing to detect them (Lakens, 2017). Effect sizes (f^2) were all below 0.013.



Bootstrapping (5,000 subsamples): T statistics with p values in parentheses.

Figure 3. Bootstrapping results: T statistics (p values)

Table 6. Hypothesis testing

Description	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	95% CI	f^2
Mobile Shopping -> Product Awareness	−0.094	−0.098	0.107	0.874	0.382	[−0.229, 0.171]	0.009
Mobile Shopping -> Brand Perception	0.109	0.120	0.096	1.137	0.256	[−0.151, 0.254]	0.012
Mobile Shopping -> Purchase Intention	0.095	0.081	0.093	1.027	0.304	[−0.136, 0.219]	0.009

Description	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	95% CI	f^2
Mobile Shopping -> Actual Purchase Behaviour	0.055	0.009	0.105	0.519	0.604	[−0.174, 0.187]	0.003
Purchase Intention -> Actual Purchase Behaviour	0.046	0.014	0.109	0.426	0.670	[−0.181, 0.179]	0.002

The acceptance–purchase gap

Table 7 shows the gap directly. Of the 111 respondents classified as acceptors, 43.2% reported completed purchase behaviour, compared with 40.8% of non-acceptors, a difference that was not significant (χ^2 = 0.06, p = 0.812). Acceptors were also no more likely to report purchase intention (42.3% vs 36.7%; χ^2 = 0.56, p = 0.455). Even among the 47 respondents who both accepted mobile shopping and intended to purchase, only 42.6% reported completed purchase behaviour, close to the rate for the whole sample (42.0%).

Table 7. Mobile shopping acceptance and purchase conversion

Group	n	Converters (APB ≥ 4)	Conversion rate (%)	Intenders (PI ≥ 4) (%)
Acceptors (MS ≥ 4)	111	48	43.2	42.3
Non-acceptors (MS < 4)	120	49	40.8	36.7
Total	231	97	42.0	39.4
Test of difference		χ^2 = 0.06, p = 0.812		χ^2 = 0.56, p = 0.455

Multigroup analysis

Permutation-based multigroup analysis compared consumers aged 45 and above (n = 141) with those under 45 (n = 89), and consumers with a hypertension diagnosis (n = 75) with those without (n = 150); respondents who were unsure of their diagnosis (n = 5) or did not respond were excluded from the second comparison. None of the ten group differences was significant (all permutation p ≥ 0.152; Table 8).

Table 8. Multigroup analysis (permutation test, 1,000 permutations)

Path	β ≥45	β <45	Diff.	p	β Dx	β No Dx	Diff.	p
MS -> PA	−0.107	−0.205	0.098	0.429	−0.218	−0.112	−0.106	0.454
MS -> BP	0.149	−0.166	0.316	0.152	0.200	0.139	0.061	0.674
MS -> PI	0.148	0.070	0.077	0.632	0.174	0.035	0.139	0.437
MS -> APB	−0.081	0.013	−0.094	0.814	0.001	−0.010	0.012	0.975
PI -> APB	0.058	0.198	−0.140	0.677	−0.118	0.118	−0.237	0.373

Dx = diagnosed with hypertension; No Dx = not diagnosed.

Table 9. Summary of hypothesis testing results

Hypothesis	Statement	Description
H1	Mobile shopping acceptance → product awareness	Not supported
H2	Mobile shopping acceptance → brand perception	Not supported
H3	Mobile shopping acceptance → purchase intention	Not supported
H4	Mobile shopping acceptance → actual purchase behaviour	Not supported
H5	Purchase intention → actual purchase behaviour	Not supported
H6	Effects differ by age group	Not supported
H7	Effects differ by diagnosis status	Not supported

The results show that mobile shopping acceptance is high but unrelated to any stage of HBPM purchase, that intention does not translate into reported behaviour, and that these patterns hold across age groups and diagnosis status.

Discussion

The central finding is a clear acceptance–purchase gap. Consumers in this sample viewed mobile shopping favourably: around two-thirds agreed that mobile tools help them search, pay, track their blood pressure and reorder. Yet this acceptance had no measurable relationship with awareness, brand perception, intention or completed purchase. Because the confidence intervals exclude effects larger than about 0.25 and out-of-sample prediction was no better than the mean, the result reflects an effect that is absent or small, not an underpowered test (Amrhein et al., 2019; Lakens, 2017).

The finding contrasts with Nigerian studies in which acceptance beliefs predicted adoption intention for digital payments and mHealth applications (Adanigbo et al., 2025; Foluke et al., 2025). The difference lies in the outcome. Those studies predicted intention to use a technology, whereas this study predicted purchase of a product through a channel. UTAUT explains why consumers accept a channel but says little about whether they then buy a clinically sensitive product through it. This is consistent with meta-analytic evidence that UTAUT relationships weaken outside the settings in which the model was developed (Blut et al., 2022).

Channel structure offers one explanation. Almost three-quarters of respondents bought their device in a pharmacy, only 2.2% bought online, and 76.6% first heard about HBPM from a pharmacist. In this market, mobile tools appear to serve as attitudes toward a convenient channel rather than as the route through which purchase happens. Consumers may research on a phone and buy in a pharmacy, as the research-shopper literature describes (Verhoef et al., 2007), but if the pharmacy visit carries the decision, acceptance of the mobile channel will not predict the purchase.

Trust and risk offer a second explanation. Buying a medical device online exposes consumers to performance and financial risk (Featherman & Pavlou, 2003), and in Nigeria fears about falsified cardiovascular products push consumers toward trusted outlets (Shedul et al., 2022). Trust is a precondition for online purchase (Gefen et al., 2003), and research on e-payment in Nigeria shows that trust and task-technology fit must both be present before acceptance leads to use (Oni et al., 2022; Goodhue & Thompson, 1995). Mobile platforms that lack clinical verification or pharmacist consultation may therefore be accepted in principle while failing the purchase task. These mechanisms were not

measured here and should be tested directly.

The absence of age and diagnosis differences is also informative. Although older consumers are often expected to face greater digital barriers (Hoque & Sorwar, 2017), the gap was no smaller among younger consumers. Similarly, clinical need did not make diagnosed consumers more likely to convert acceptance into purchase. The gap therefore appears to be a feature of the market rather than of particular consumer segments; the high education level of the sample may also explain why age did not differentiate them. Finally, the non-significant link between intention and behaviour departs from the well-established positive relationship in the literature (Sheeran, 2002). Part of the explanation may lie in measurement: both the intention and the behaviour items were framed around multichannel purchase journeys in general rather than a specific, recent purchase, so they may refer to different purchase episodes. This result should be treated with caution until it is replicated with behaviour measures tied to a specific, recent purchase.

The study contributes to the literature in three ways. It extends UTAUT research to health-device purchase in an emerging market and shows that acceptance of a channel is not sufficient for purchase through it. It demonstrates the value of a staged purchase outcome, which reveals that mobile acceptance has no effect at any stage rather than at only one. And it shows how confidence intervals, out-of-sample prediction and multigroup tests can turn non-significant results into an informative boundary condition.

5. Conclusions, Implications, Limitations, and Recommendations

5.1 Conclusions

This study examined whether mobile shopping acceptance drives the purchase of HBPM devices in Lagos, Nigeria. Acceptance was high but had no significant effect on product awareness, brand perception, purchase intention or actual purchase behaviour, and the absence of effects held across age groups and diagnosis status. In a market anchored in pharmacy purchase, mobile acceptance functions as a channel attitude rather than as a purchase driver.

5.2 Implications

Results for theory indicate an online/offline boundary condition for UTAUT: In health-device markets where trust and clinical assurance are provided offline, adoption of an online channel is not related to use of that channel for purchase. Trust, perceived risk, and task-technology fit should be among the required enablers for health product acceptance models in the future.

HBPM brand and retail staffs should not take high mobile acceptance as a measure to increase mobile investment sales for practice. Mobile platforms are more likely to convert if they mimic the consumer's peace of mind acquired in the pharmacy: authentic product verification, allowing users to consult with a pharmacist in the app and provide them with links to a trusted pharmacy for either collection or assistance. Respondents most preferred the BP-tracking apps, and it could be incorporated with purchase/reorder functionality for digital pharmacies. Results indicate that spreading the uptake of HBPM must continue via pharmacists, as this is the primary source of awareness and the sale of HBPM.

5.3 Limitations and Recommendations

This study has limitations that can be used as topics for further research. First, it was not a measure of the mechanisms suggested to explain the gap (those mentioned above, such as, but not limited to, trust, perceived risk, task-technology fit, among others) which ought to be explored in future research as mediators of this gap. Second, this was a self-reported

measure of acceptance and a cross sectional design limited causal inferences. The acceptance could be predicted based on purchase with a longitudinal or transaction design. Third, the sample predominantly consisted of health retailers who were online, and thus, the results reflect an environment where the online presence of health retailers is prevalent, which may not be true in regions where online health retail is more mature than the study sample. Fourth, the sample had a high education level and was from a single state and this restricts generalisation. Fifth, because there is no intention–behaviour relationship, there is a need to replicate with items of behaviour associated with a specific purchase. Other health devices, as well as other markets with varying levels of dependence on pharmacists, should also be compared to HBPM in future studies.

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