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Mobile OS and willingness to pay in quick commerce

Abstract

Research background and purpose: Quick commerce - delivery within 60 minutes - has expanded rapidly across digital retail, but margins remain thin where delivery fees compete against dense networks of physical stores. Operators charging these fees need a way to identify which consumers will pay them, using only the data the platform already has. This study tests whether mobile operating system (iOS vs. Android) serves as a valid segmentation criterion in the Polish q-commerce market. No prior study has tested the OS-as-proxy hypothesis in a grocery or delivery-fee context. Several operators have already exited the Polish market, and a segmentation strategy that costs nothing to implement - OS is already visible at checkout - has direct implications for surviving operators.

Design/methodology/approach: A Computer-Assisted Web Interviewing (CAWI) survey of 1,000 mobile users in Poland (2025) was used to test three hypotheses concerning iOS/Android differences in willingness to pay for standard delivery (H1), speed surcharges (H2), and the independence of any OS effect from household income (H3). Data were analysed using Mann-Whitney U tests and ordinal logistic regression with demographic controls.

Findings: H1 was not supported in either group - the estimated iOS effect is directionally consistent with the hypothesis but statistically inconclusive given limited power. H2 was rejected: the only significant OS effect runs counter to the prediction, with Android users showing higher willingness to pay for faster delivery than iOS users. H3 was confirmed: OS and declared income are statistically independent, ruling out income confounding and pointing toward service context as the primary boundary condition.

Value added and limitations: OS may be a structurally weak income proxy in markets where Android spans the full device price spectrum. Device value should be tested as a potentially more appropriate segmentation construct. The study is limited to Poland, a market with exceptionally high retail density, and employs a cross-sectional design.

Keywords: *quick commerce, willingness to pay, mobile operating system, consumer segmentation, iOS, Android*

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1. Introduction

1.1. Q-commerce as the fastest-growing e-commerce segment

Quick commerce - defined as e-commerce with delivery windows of under 60 minutes - has emerged as one of the fastest-growing segments of digital retail. The global q-commerce market reached $129.73 billion in 2025 and is projected to grow to $358.16 billion by 2030, representing a compound annual growth rate of 22% (The Business Research Company, 2026). This growth is driven by rising consumer expectations for on-demand convenience, the proliferation of dark stores as hyperlocal fulfilment infrastructure, and the expansion of app-based ordering platforms into grocery and Fast-Moving Consumer Goods (FMCG) categories dominated by physical retail.

Poland's exceptional retail density creates a structurally distinct environment for q-commerce. With 130,500 FMCG stores in 2024-compared to Germany's 58,000 stores serving more than twice the population-Poland has exceptionally high retail density (Łagutko, 2025). This density creates low transaction costs for physical grocery shopping, establishing a competitive reference point that q-commerce operators must overcome through speed, convenience, and strategic pricing. The Polish market has seen both the entry and exit of major operators: Gorillas, Jokr, and Swyft all ceased operations, while Żabka Jush and Lisek remain active, alongside platform-based models operated by Glovo, Wolt, and Carrefour.

This density makes Poland an unusually diagnostic setting for testing device-based WTP segmentation. The near-zero-cost physical alternative that Prospect Theory identifies as the mechanism suppressing loss-framed fee tolerance (Section 2) is not abstract in Poland. A convenience store within a few minutes' walk - typically a Żabka - is simply how most people shop. If device-based segmentation breaks down anywhere, this is where the theory predicts it should break down first.

The value proposition of q-commerce rests on time compression: the service substitutes for an unplanned trip to a convenience store, monetising the consumer's willingness to pay for immediacy rather than price discounts. Unlike standard e-grocery, where next-day delivery competes on assortment and price, q-commerce competes on speed alone - and charges explicitly for it through delivery fees and minimum order thresholds. Understanding which consumers are willing to pay these fees, and what observable variables predict that willingness, is therefore a question of direct commercial relevance for q-commerce operators in Poland.

This study tests whether mobile operating system can serve as a pricing segmentation variable for q-commerce delivery fees in Poland - a market where exceptional retail density puts on-demand delivery in direct competition with a near-costless alternative, and where OS, unlike self-reported measures, is observable without bias.

1.2. The segmentation problem: limits of self-reported demographics

Consumer segmentation based on mobile operating system has attracted growing attention in marketing research and practice. The core argument is simple: iOS and Android users differ systematically in income, spending habits, and attitudes - and these differences are observable from panel metadata without any survey questions. Device type is available for 100% of mobile respondents, requires no self-reporting, and is free from the aspirational inflation that affects declared income measures. For platforms collecting data through mobile panels, OS is therefore a technically attractive segmentation variable.

The empirical case for OS-based segmentation rests primarily on evidence from app markets and digital subscription services. In these contexts, iOS users consistently show lower price sensitivity and higher in-app spending than Android users (Ghose & Han, 2014). The mechanisms behind this pattern are reviewed in Section 2.1. What matters here is that the evidence base is real, consistent, and comes from credible sources - which makes it a reasonable starting point for extending device-based segmentation to new service contexts.

Whether these mechanisms transfer to a functional, necessity-driven service context is an open theoretical question. It is also a question with a price tag: q-commerce operators set delivery fees today, and delivery fee pricing is among the most consequential decisions they face (Gosling et al., 2025). App markets sell discretionary purchases. Q-commerce sells milk and bread someone ran out of.

Empirical evidence that OS-based personalization is already deployed in e-commerce comes from Hannak et al. (2014), who audited 16 major US retail and travel websites for price steering and discrimination. The study finds that Travelocity modifies hotel prices for iOS Safari users - lowering prices by approximately $15 on 5% of results - without any visible signal to the consumer. Home Depot serves a different, higher-priced product set to mobile browsers than to desktop users. These findings establish that device type, including operating system, is an actively used input to e-commerce personalization algorithms. Whether such OS-based differentiation reflects genuine differences in consumer willingness to pay - or merely exploits an assumed correlation - remains untested in the q-commerce context.

The economic stakes of delivery fee sensitivity in this context are substantial. A large-scale consumer survey found that over 90% of consumers are likely to abandon an online purchase when faced with high shipping costs, and approximately 50% report unwillingness to pay any delivery fee regardless of speed (Gosling et al., 2025). Whether Polish consumers - operating in a market where the high density of traditional retail outlets provides a near-zero-cost physical alternative - exhibit comparable sensitivity (Łagutko, 2025), and whether that sensitivity varies by device type, is what this study investigates. Early survey evidence from the Lubuskie voivodeship confirms that Polish consumers pay close attention to price and delivery terms when making online purchase decisions, and identify high delivery costs as a barrier to more frequent online shopping (Kułyk & Michałowska, 2016).

1.3. Mobile OS as an objective proxy

Consumer segmentation variables differ in how they are measured. Declared income, the most commonly used proxy for spending capacity in survey research, is a self-reported variable subject to high non-response, documented in detail in Section 2.3. Mobile operating system avoids this problem by construction: it is captured from device metadata rather than self-reported, so respondents' willingness to answer does not affect its measurement. Section 3.2 details how OS was extracted for this study.

Beyond its measurement advantages, OS is theoretically motivated as a segmentation variable. The literature reviewed in Section 2.1 suggests that iOS ownership is associated with higher spending capacity and lower price sensitivity among iPhone users. This prediction finds empirical support at both the individual and aggregate level. Keusch et al. (2023), using a probability-based national survey in Germany (N=13,703), confirm that iPhone owners differ systematically from Android owners not only in income and employment, but also in attitudes and life satisfaction - differences that persist after controlling for age, education, and region. At the aggregate level, Ucar et al. (2021) find that iOS device usage positively correlates with higher income and education across French geographic areas, while Android usage shows the opposite pattern.

1.4. Research gap and hypotheses

No published study has examined mobile operating system as a predictor of willingness to pay for delivery in the Polish q-commerce market. The broader literature on iOS/Android differences - reviewed in Section 2.1 - identifies several mechanisms linking device ownership to spending behaviour, and all point toward higher willingness to pay among iOS users. These mechanisms are well established individually, but they have not been tested together in a new service context, so their combined effect here is not guaranteed.

Q-commerce offers a useful test case. It is a digital service delivered through a mobile app, which on the surface resembles the app markets and subscription services where iOS/Android differences have been consistently documented. The purchase, however, is driven by immediate need rather than discretionary preference: consumers order groceries because they need them, not because they want a digital experience. Whether the mechanisms documented in hedonic app markets transfer to this more functional setting is the question this study addresses.

Within the Prospect Theory framework developed in Section 2, delivery fees are coded as losses relative to the zero-cost physical retail alternative. iOS ownership is theorised to moderate this loss coding: habitual, frictionless spending within the Apple ecosystem may shift the reference point upward, so the fee registers as a smaller loss. If this moderation holds, iOS users should show higher WTP for both standard delivery and speed surcharges. H3 tests whether any such effect works through income - the wealth-selection channel - or independently of it.

H1. *iOS users display higher willingness to pay for standard delivery than Android users, both among active q-commerce users and among aware non-users.*
H2. *iOS users display higher willingness to pay a surcharge for faster delivery than Android users, among active q-commerce users.*
H3. *The OS effect on willingness to pay is independent of declared household income.*

The remainder of the paper tests these hypotheses empirically and discusses the conditions under which OS-based segmentation may or may not be informative.

2. Literature review

Within Prospect Theory (Kahneman & Tversky, 1979), consumers evaluate outcomes not in absolute terms but against a reference point, and losses are weighted more heavily than equivalent gains. In the Polish market, where physical grocery shopping costs next to nothing (Section 1.1), that near-zero baseline becomes the reference point for everyday grocery acquisition. A delivery fee is therefore not evaluated as a fair price for a service - it is a deviation from a costless alternative, and it registers as a loss. Loss aversion predicts resistance to that loss even among consumers with sufficient spending capacity.

Loss aversion explains why the fee registers as a loss at all; a second mechanism, Thaler's (1985) mental accounting, explains why that loss feels isolated rather than absorbed into the purchase. Consumers do not fold the delivery fee into the total basket value - they open a separate mental account for it. A PLN 10 fee on a PLN 50 basket does not register as a marginal cost increase on the purchase; it registers as a standalone PLN 10 loss. Loss aversion alone predicts resistance to the fee; mental accounting predicts that the resistance runs deeper, because the fee is never weighed against the basket it belongs to.

The two WTP constructs tested in this study are not equivalent under this framework. A standard delivery fee is an obligatory charge, loss-coded by default. A speed surcharge is different: the consumer is not paying to receive the order, but to receive it sooner. Costs framed as the price of an added benefit meet less resistance than the same cost framed as a condition of service. H1 and H2 are tested separately for this reason. The distinction also leaves room for OS moderation to operate differently across the two fee types - a question the results in Section 4 return to.

The OS moderation mechanism introduced in Section 1.4 operates on this reference point directly: if habitual App Store spending shifts it upward for iOS users, delivery fees should register as smaller losses regardless of income. H1 and H2 test this prediction; H3 isolates it from the income channel.

2.1. iOS/Android as proxies for economic status and consumption patterns

Three independent bodies of evidence suggest that iOS users should exhibit higher willingness to pay for digital services than Android users. Each rests on a different mechanism, and all three point in the same direction.

The first mechanism is wealth selection. iPhones cost substantially more than Android devices. According to IDC's Worldwide Quarterly Mobile Phone Tracker (2025), the average selling price of an iOS device reached $1,045 in 2024, compared to $297 for Android - a 3.5-fold gap. This price difference acts as a filter: people who own iPhones tend to have more money. Bursztyn et al. (2025) confirm that this income signal is socially recognised - in a U.S. sample, Android users were perceived to earn 10.5% less than iPhone users. This gap is not limited to perceptions. Using a probability-based national survey in Germany (N=13,703), Keusch et al. (2023) find that iPhone owners are systematically overrepresented in higher income brackets and among employed respondents, even after controlling for age, education, and region. At the aggregate level, Ucar et al. (2021), analysing 3.7 billion mobile traffic records from France, find that iOS device usage is positively associated with higher income and education across geographic areas, while Android usage shows the opposite pattern. Wealthier consumers are generally less sensitive to prices - including delivery fees.

A second channel runs through payment habituation rather than wealth. iPhone users live inside a payment infrastructure - the App Store, Apple Pay, one-tap subscriptions - that makes spending feel effortless. Repeated small payments lower the psychological cost of spending over time. In mobile app markets, the price elasticity of demand is approximately −0.20 among iOS users but −0.84 among Android users (Ghose & Han, 2014) - a fourfold difference indicating that Android users are substantially more responsive to price changes than their iOS counterparts. If this habit carries over to other digital services, iOS users should also show less resistance to delivery fees. Supporting evidence comes from a study of m-commerce perceptions: Ünal et al. (2015), using a sample of university students in Turkey (N=287), find that iOS users score significantly higher than Android users on usefulness, ease of use, security, actual use, and intention to use m-commerce applications. Even within the iOS ecosystem, the relationship between income and spending is non-linear: analysing over 776 million App Store purchases, Kooti et al. (2017) find that income has negligible effect on in-app spending across most of the income distribution, with meaningful differences only at the extremes - below $20k and above $140k annually. The wealth-selection mechanism, then, is not a simple income-to-spending translation. Ecosystem habituation may do more of the work in shaping iOS spending patterns than purchasing power alone.

The last mechanism is status signalling. The iPhone is not just a phone - it is a social object. Bursztyn et al. (2025) asked U.S. college students how much money they would need to accept having their messages appear as green bubbles - the visual mark of a non-iPhone user. The average answer was $49, and 90% associated green bubbles with negative social judgement. iPhone ownership carries a status premium that its users actively protect.

Not all evidence points in the same direction, however. Götz et al. (2017), in a multinational study of smartphone users (N=1,081), found that iOS and Android users differ only minimally in personality traits and sociodemographic characteristics. Monthly budget emerged as the only significant predictor of OS, with an odds ratio of 0.922 - barely distinguishable from no effect. The authors conclude that while minor differences exist, they are of negligible practical magnitude. This does not rule out the wealth selection mechanism. It does mean the income-based distinction between iOS and Android users may be weaker than marketing practice tends to assume.

2.2. Willingness to pay for delivery in e-commerce and q-commerce

Research on consumers' willingness to pay for grocery delivery services remains limited relative to the scale of the market. Van Droogenbroeck and Van Hove (2022), in a study of Belgian click-and-collect users and non-users (N=572), find that perceived time pressure does not translate into a higher maximum willingness to pay per order among active users - the effect appears only in annual WTP, mediated by higher order frequency. Household income shows a positive but weak effect, significant only at the 10% level in the users subsample. These findings suggest that the intuitive assumption linking consumer affluence to higher delivery fee tolerance may be more fragile than commonly assumed. Consistent with this, Nguyen et al. (2019), using conjoint analysis among Dutch online shoppers (n=692), find that delivery fee dominates all other delivery attributes - including speed - in shaping consumer preferences, accounting for approximately 64% of the overall importance score. Consumer segments defined by gender and income show distinct preference structures, with price sensitivity highest among female and low-income consumers. This evidence suggests that delivery fee sensitivity is a robust cross-market phenomenon, though its interaction with consumer characteristics remains context-dependent. Notably, Van Droogenbroeck and Van Hove conduct separate analyses for active users and aware non-users - a design choice adopted in the present study, given that q-commerce WTP is conceptually distinct across the two groups.

At the same time, delivery time accuracy emerges as a key driver of repurchase behaviour in q-commerce. Harter et al. (2025), analysing over two million orders from a Western European food delivery service, find that late deliveries significantly shorten the time until a customer's next order, with the effect mediated by customer satisfaction. Speed, in other words, is a service-defining attribute in q-commerce - consumers protect its value through repeat purchase decisions, whether or not they'd say so if asked directly.

Q-commerce introduces a time compression premium that standard e-commerce delivery research does not address. Studies on delivery fee sensitivity are concentrated in Western European and North American markets, with Central and Eastern Europe substantially underrepresented. The general e-commerce baseline sensitivity to shipping costs, discussed in Section 1.2 (Gosling et al., 2025), sets the benchmark against which q-commerce operators must position their fee structures. Whether Polish consumers - operating in a market with an unusually low-cost physical alternative - reproduce this baseline sensitivity, or diverge from it, is addressed empirically in Section 4 and revisited in Section 5.3.

The relationship between income and price sensitivity in delivery contexts is further complicated by the nature of the consumption occasion. Wakefield and Inman (2003), across three studies combining scanner data, consumer surveys, and field observation, demonstrate that price sensitivity is systematically lower for hedonic than for functional consumption occasions, and that income moderates this effect: higher-income consumers show markedly reduced price sensitivity specifically in hedonic contexts, while low-income consumers remain price-sensitive regardless of occasion. Q-commerce occupies an ambiguous position on the hedonic-functional continuum - it delivers everyday grocery items (functional) through a convenience-driven, on-demand channel (hedonic framing). This ambiguity may compress WTP variance across income segments in ways that standard grocery or general e-commerce studies do not anticipate, motivating the search for segmentation variables beyond declared income.

2.3. Limitations of declarative data and the case for objective measures

Income questions consistently yield among the highest item non-response rates in survey research. Tourangeau and Yan (2007) document that income and financial asset questions produce missing data rates of 20-40% across national surveys, attributing this pattern to respondents' perception of income questions as intrusive - a reaction triggered regardless of the respondent's actual financial situation. Moore et al. (2000), in a review of U.S. government income surveys, report imputation rates of 26% for wage and salary income and over 44% for asset income in the Current Population Survey. In the present study, 16.32% of respondents declined to provide household income data - a rate below these documented benchmarks, likely reflecting the anonymous CAWI format. Regardless of the absolute level, one in six respondents effectively excluded themselves from income-based segmentation models. This is precisely the gap an alternative variable with full sample coverage is meant to close.

3. Methods

3.1. Research design and data collection

Data were collected using CAWI - a self-administered online survey method in which respondents complete a structured questionnaire through a web browser without interviewer assistance. The sample was drawn from a nationally representative online panel (SW Research, Poland, N=1,000 mobile respondents), in accordance with the quality standards of the Polish Market and Opinion Research Society (PTBRiO). SW Panel, one of the largest Polish online access panels, served as the sampling frame. As of the data collection period, the panel comprised over 380,000 registered members who provided informed consent to participate in survey research. Panel membership is restricted to verified individuals; each panellist may complete a given survey only once, and automated bot submissions are technically prevented. The panel undergoes annual quality audits by OFBOR (Polish fieldwork quality organisation) and holds a CAWI quality certificate since 2015. The panel's demographic structure is regularly adjusted to match the Polish adult population. Panellists were informed that the survey was conducted as part of academic research. The sampling frame was therefore the SW Panel population of Polish internet users aged 18+, with recruitment carried out through the panel's standard invitation system. The study adhered to ethical standards for consumer research.

The CAWI method was the appropriate choice for this population: q-commerce is a post-adoption digital service, and both its use and its conscious rejection presuppose internet access - restricting the sample to online panel members therefore aligns the sampling frame with the target population rather than limiting it.

The original sample comprised N=1,465 respondents. Two cleaning stages reduced the analytic sample to N=1,409 (96.18% retention). In the first stage, 35 observations (2.39%) collected during the pre-validation testing phase were removed - their postal codes did not conform to the required XX-XXX format. In the second stage, 21 observations (1.47%) with missing values on demographic variables were excluded.

Survey routing was governed by question P2 (awareness and use of q-commerce services). Respondents were directed to one of three paths: active users (regular or occasional) proceeded to Section A (P3-P16); aware non-users proceeded to Section B (P17-P25); unaware respondents completed only the demographic module (P26-P30). This architecture ensures that WTP items are administered only to respondents with relevant service knowledge. Subsample sizes vary across analyses due to routing and response exclusions: n=495 for H1 among active users, n=465 for H2 after excluding respondents who reported not using speed surcharge services, and approximately n=420 and n=200 for aware non-users respectively. Regression models use complete cases, accounting for minor differences between Mann-Whitney and ordinal logistic regression sample sizes.

3.2. Key variable: mobile operating system

The mobile operating system variable was extracted automatically from the technical metadata of the SW Research panel at the time of survey completion. It was not declared by the respondent and is therefore free from aspirational inflation and non-response bias - available for 100% of the original sample.

The initial OS distribution in the full sample (N=1,409) comprised: Android (853), iOS (147), Windows (385), and other systems (22 combined). Desktop and non-mobile operating systems (n=407) were excluded from all analyses. The analytic sample is restricted to mobile respondents: N=1,000 (Android: 853; iOS: 147). The iOS subsample size (n=147, 14.7%) reflects the structure of the Polish smartphone market rather than a sampling artifact. According to Smart Barometr 2025, a representative consumer survey conducted in Poland (N=1,000; bolttech Poland, 2025), iOS accounts for 12% of the domestic smartphone market - consistent with the distribution observed in the present study.

The OS variable identifies the operating system of the device used to complete the survey - not necessarily the device used for q-commerce purchases. Any discrepancy between survey OS and purchase OS constitutes non-differential misclassification, which statistically attenuates rather than inflates observed effects. The practical impact of this limitation is however bounded by the structure of Polish smartphone ownership: 73% of Polish consumers use a single device exclusively (bolttech Poland, 2025), making discrepancies between the survey device and the purchase device unlikely in the majority of cases. Additionally, all q-commerce operators referenced in the survey instrument (Żabka Jush, Glovo, Wolt, UberEats, Lisek) are app-first services whose primary ordering channel is the mobile application. While web-based ordering exists for some operators, the convenience-driven, on-demand nature of q-commerce purchases makes mobile the dominant interface for this service category, further reducing the likelihood of discrepancy between the survey device OS and the purchase device OS.

By contrast, the household income variable (P28) suffers from the opposite problem: 16.32% of respondents declined to provide income data. The OS variable eliminates this non-response problem entirely, while introducing its own clearly bounded measurement constraint. The methodological case for OS as a segmentation variable is documented by Keusch et al. (2023), who show that smartphone OS is available for the full sample without non-response bias, while income variables suffer from substantial missing data even in probability-based surveys.

The group imbalance between Android (n=853) and iOS (n=147) users reflects the actual structure of the Polish smartphone market and does not compromise the validity of the statistical comparisons. Mann-Whitney U tests make no assumption of equal group sizes and remain valid under substantial imbalance. Ordinal logistic regression likewise does not require balanced groups - coefficient estimates and standard errors are asymptotically valid regardless of group size ratio. The smaller iOS subsample does, however, reduce statistical power for detecting small effects, a limitation addressed explicitly in the post hoc power analysis reported in Section 4.2.

3.3. Dependent and control variables

Willingness to pay for standard delivery was measured by P15 (active users) and P25 (aware non-users) using an identical five-point ordered scale. The exact question wording was: *"What is the maximum delivery fee you would be willing to pay for an order worth PLN 50?"* Response options were: PLN 0 (free delivery only) / PLN 1-3 / PLN 4-6 / PLN 7-10 / above PLN 10. The PLN 50 basket reference was embedded in the question stem to provide a common consumption context across all respondents. Willingness to pay a surcharge for faster delivery was measured by P10 (active users) and P23 (aware non-users). The exact question wording was: *"Would you be willing to pay an additional fee for faster delivery?"* Response options were: yes, always / yes, in certain situations / no / I do not use such services. The last category was treated as a routing response and excluded from analysis, yielding an effective three-point ordinal scale (no / yes, conditionally / yes, always) for the Mann-Whitney and ordinal regression analyses. Customer satisfaction was measured by P13 (active users only) on a standard five-point Likert scale.

Four demographic variables served as controls in all regression models: age (P26, five categories), education (P27, four categories), household net income (P28, four income brackets plus declined-to-answer), and settlement size (P29, four categories).

3.4. Analytical methods

All analyses were conducted in R Studio. The analytical strategy proceeded in six steps: (1) chi-squared tests of OS-demographic associations; (2) Mann-Whitney U tests for the bivariate comparison of WTP distributions; (3) proportional odds logistic regression (polr, MASS package) with demographic controls; (4) likelihood ratio tests for the OS × income interaction; (5) robustness diagnostics, including the Brant test and multicollinearity checks; and (6) effect-size interpretation based on odds ratios, 95% confidence intervals, and a post hoc power assessment for the focal OS contrast. This extended strategy was adopted to reduce overreliance on p-values and to distinguish between the absence of robust evidence and evidence of no effect.

Before interpreting the results of the ordinal logistic regression models, the proportional odds assumption (parallel regression assumption) was tested. This is a critical diagnostic step to ensure that the relationship between the predictors (OS, income, etc.) and the willingness to pay remains consistent across all levels of the dependent variable. Multicollinearity was assessed using Variance Inflation Factors (VIF); all values were below 1.31, indicating no redundancy among predictors.

4. Results

4.1. Sample characteristics and OS-demographic associations

The analytic mobile sample (N=1,000) comprises 853 Android users (85.3%) and 147 iOS users (14.7%).

Table 1 presents the full sample breakdown by operating system across all demographic and routing variables.

Table 1. **Sample characteristics and OS-demographic associations (mobile respondents, N=1,000)**

Variable	Category	Android n (%)	iOS n (%)	Total n (%)	χ^2	df	p
Age	18-24	136 (15.9)	45 (30.6)	181 (18.1)	41.38	4	<0.001
	25-34	205 (24.0)	55 (37.4)	260 (26.0)			
	35-44	251 (29.4)	23 (15.6)	274 (27.4)			
	45-54	148 (17.4)	15 (10.2)	163 (16.3)			
	55+	113 (13.2)	9 (6.1)	122 (12.2)			

Education	Primary/lower secondary	53 (6.2)	12 (8.2)	65 (6.5)	4.98	3	0.173
	Secondary	405 (47.5)	59 (40.1)	464 (46.4)			
	Higher	276 (32.4)	59 (40.1)	335 (33.5)			
	Vocational	119 (13.9)	17 (11.6)	136 (13.6)			
Household income	Below PLN 5,000	227 (26.6)	32 (21.8)	259 (25.9)	2.98	4	0.562
	PLN 5,000-8,000	210 (24.6)	43 (29.3)	253 (25.3)			
	PLN 8,001-12,000	182 (21.3)	33 (22.5)	215 (21.5)			
	Above PLN 12,000	88 (10.3)	17 (11.6)	105 (10.5)			
	Declined to answer	144 (16.9)	21 (14.3)	165 (16.5)			
Settlement size	Rural / town <50k	367 (43.0)	55 (37.4)	422 (42.2)	15.25	3	0.002
	50k-200k	277 (32.5)	36 (24.5)	313 (31.3)			
	200k-500k	102 (12.0)	21 (14.3)	123 (12.3)			
	>500k	107 (12.5)	35 (23.8)	142 (14.2)			
Survey route	Active user	422 (49.5)	73 (49.7)	495 (49.5)	-	-	-
	Aware non-user	357 (41.9)	63 (42.9)	420 (42.0)			
	Unaware	74 (8.7)	11 (7.5)	85 (8.5)			

Note: percentages within each OS group. Three respondents (Android=2, iOS=1) did not select any income response option and are excluded from the income distribution row. All other rows sum to full subsample totals. Chi-square tests assess OS-demographic associations. Survey route not tested (routing is outcome of P2, not a demographic variable).

Source: own elaboration

The Brant test was performed on the primary model (H1). This test was selected over score and likelihood ratio alternatives because simulation studies show it controls type I error better in small samples, which is relevant given the iOS subsample size of n=147 (Liu et al., 2023). As shown in Table 2, the omnibus test result was non-significant ($\chi 2=60.19, p=0.060$), which indicates that the proportional odds assumption was not violated. Furthermore, the test for the mobile operating system (iOS vs. Android) specifically showed no violation ($p=0.143$). These diagnostic results confirm that the ordered logit estimator (polr) is appropriate for this dataset.

Table 2. **Brant Test Results for the Proportional Odds Assumption**

Variable	χ^2 (Chi-Square)	df	p-value
Omnibus (Model total)	60.19	45	0.060
Mobile OS (iOS)	5.43	3	0.143
Age	11.22	12	0.510*
Household Income	16.96	12	0.151*
Education	10.70	9	0.297*
Settlement size	9.61	9	0.383*

***Note**: For demographic control variables, the table presents the aggregate results for all factor levels. P>0.05 indicates the assumption holds.

Source: own elaboration

Chi-squared tests revealed a significant association between OS and age (χ^2=41.38, df=4, p<0.001): iOS users are markedly younger, with 30.6% aged 18-24 versus 15.9% among Android users. OS also differs significantly by settlement size (χ^2=15.25, df=3, p=0.002): iOS users are overrepresented in metropolitan areas above 500,000 inhabitants (23.8% vs. 12.5%). No significant associations were found between OS and education (χ^2=4.98, p=0.173) or household income (χ^2=2.98, p=0.562). The income distribution is nearly identical across OS groups.

4.2. Willingness to pay for delivery

Among active users, the Mann-Whitney test on P15 yielded W = 14,163, p = 0.074, which means that the difference between iOS and Android users was not statistically significant at the 0.05 level. In the ordinal logit model, the coefficient for iOS was positive (β = 0.411, SE = 0.230, p = 0.074). This gives an odds ratio of 1.51, with a 95% confidence interval from 0.96 to 2.37. A post hoc power analysis was conducted for H1 in R. With an active user sample of n=495 (Android=416, iOS=79), α=0.05, and a small effect size (Cohen's d=0.2), the achieved power was 0.61. This indicates that the study was underpowered to reliably detect small effects of OS on standard delivery WTP. The null result for H1 must therefore be interpreted as statistically inconclusive rather than as evidence of no effect - the observed OR=1.51 [0.96, 2.37] is directionally consistent with the hypothesis but falls short of conventional significance thresholds. For H2, where a significant effect was detected (p=0.037), power is not a limiting concern.

Table 3. **Ordinal logistic regression results - full model (all predictors)**

Predictor	H1 - WTP delivery active users (n≈491)			H1 - WTP delivery non-users (n≈418)			H2 - Speed surcharge active users (n≈465)			H2 - Speed surcharge non-users (n≈200)		
	OR	95% CI	p	OR	95% CI	p	OR	95% CI	p	OR	95% CI	p
Mobile OS (iOS vs. Android)	1.51	[0.96, 2.37]	0.075†	0.89	[0.53, 1.49]	0.650	0.59	[0.35, 0.96]	0.037*	2.07	[0.90, 4.78]	0.089†
Age: 25-34 (ref: 18-24)	1.02	[0.63, 1.63]	0.946	1.33	[0.72, 2.48]	0.361	0.70	[0.41, 1.19]	0.193	1.13	[0.49, 2.61]	0.779
Age: 35-44	1.00	[0.60, 1.68]	0.992	0.80	[0.44, 1.47]	0.473	0.81	[0.46, 1.43]	0.468	0.76	[0.33, 1.75]	0.521
Age: 45-54	1.18	[0.66, 2.10]	0.574	0.64	[0.33, 1.25]	0.192	1.30	[0.69, 2.47]	0.414	0.40	[0.16, 0.98]	0.048*
Age: 55+	1.12	[0.55, 2.27]	0.754	0.53	[0.27, 1.04]	0.065†	0.45	[0.21, 0.95]	0.038*	0.58	[0.23, 1.42]	0.234
Education: Secondary (ref: Primary)	3.33	[1.51, 7.34]	0.003**	0.33	[0.15, 0.69]	0.003**	1.15	[0.47, 2.85]	0.766	0.95	[0.33, 2.73]	0.927
Education: Higher	2.40	[1.07, 5.41]	0.034*	0.27	[0.12, 0.60]	0.001***	1.04	[0.41, 2.66]	0.930	0.94	[0.31, 2.87]	0.913
Education: Vocational	3.27	[1.36, 7.88]	0.008**	1.46	[0.62, 3.42]	0.386	2.16	[0.81, 5.86]	0.126	3.10	[0.97, 9.94]	0.057†
Income: 5k-8k (ref: <5k)	0.87	[0.55, 1.36]	0.534	0.64	[0.38, 1.06]	0.084†	1.58	[0.96, 2.59]	0.070†	0.43	[0.21, 0.89]	0.024*
Income: 8k-12k	0.93	[0.59, 1.46]	0.757	1.45	[0.85, 2.46]	0.170	1.34	[0.81, 2.22]	0.258	0.69	[0.33, 1.44]	0.330
Income: >12k	0.90	[0.51, 1.60]	0.722	1.21	[0.61, 2.36]	0.585	1.18	[0.62, 2.24]	0.612	0.94	[0.40, 2.22]	0.893
Income: declined	0.62	[0.36, 1.09]	0.097†	0.74	[0.42, 1.27]	0.273	0.62	[0.34, 1.14]	0.127	0.58	[0.26, 1.30]	0.187

Settlement: 50k-200k (ref: >500k)	1.16	[0.72, 1.86]	0.536	1.12	[0.56, 2.23]	0.753	1.24	[0.73, 2.10]	0.435	2.03	[0.77, 5.64]	0.162
Settlement: 200k-500k	1.16	[0.67, 2.00]	0.596	1.19	[0.53, 2.71]	0.674	0.89	[0.49, 1.62]	0.702	1.09	[0.32, 3.79]	0.884
Settlement: rural/<50k	1.44	[0.89, 2.34]	0.137	1.09	[0.57, 2.09]	0.798	1.09	[0.64, 1.87]	0.740	2.83	[1.10, 7.62]	0.034*

Note. OR = odds ratio; 95% CI in brackets. Reference categories: Android, age 18-24, primary/lower secondary education, income PLN 5,000-8,000, settlement >500k. ǂ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Source: own elaboration

Among aware non-users, education shows a pattern absent in the active-user model (Table 3). Respondents with secondary (OR=0.33, p=0.003) and higher education (OR=0.27, p=0.001) declared lower hypothetical WTP for standard delivery than the primary/lower secondary reference group. This negative education gradient among non-users - absent in the active-user model - may reflect a selection effect: more educated consumers who are aware of q-commerce but have chosen not to use it may be precisely those who evaluated the service and found the delivery fee unjustifiable relative to the physical retail alternative. This interpretation is consistent with the Polish retail density context but cannot be confirmed with the present cross-sectional data.

4.3. Willingness to pay a surcharge for faster delivery

Among active users (n=465: Android=392, iOS=73), the Mann-Whitney test on P10 yielded W=16,390, p=0.030. The result is statistically significant, but directionally reversed: Android users showed higher willingness to pay a speed surcharge than iOS users. Both groups share the same median response (“yes, in certain situations”; Mdn=2, Q1=1, Q3=2), but the distributions differ at the tails: 16.3% of Android users declared unconditional willingness to pay (“yes, always”) compared to 6.8% of iOS users, while iOS users more frequently declined entirely (43.8% vs. 33.9%). It is this difference in the upper tail of the distribution that drives the Mann-Whitney result. Ordinal regression confirms the direction: $\beta=-0.534$ (SE=0.256, t=–2.089, p=0.037). Among aware non-users, W=3,561, p=0.163; not significant. H2 is rejected; the significant effect runs counter to the hypothesis.

4.4. Independence of OS effect from declared income

The likelihood ratio test comparing the interaction model (OS × income) against the base model yields χ^2=1.54 (df=4, p=0.820). All four OS × income interaction coefficients are non-significant (p range: 0.43-0.77). H3 is confirmed: the OS effect is independent of declared income. This result must be read in conjunction with H1 and H2: the effect that is income-independent is itself non-significant (H1) or directionally reversed (H2).

4.5. Customer satisfaction

The Mann-Whitney test on P13 yields W=16,168, p=0.984. Mean satisfaction scores: Android=3.84, iOS=3.85. Operating system does not differentiate customer satisfaction.

Table 4. **Mann-Whitney test results by hypothesis**

Hyp.	Variable / Sample	W	p-value	Direction	Result
H1	WTP delivery (P15) - active users, n=495	14,163	0.074	iOS > Android (ns)	Not confirmed
	WTP delivery (P25) - aware non-users, n=420	10,980	0.831	-	Not confirmed
H2	Speed surcharge (P10) - active users, n≈465	16,390	0.030	Android > iOS *	Rejected (reversed)
	Speed surcharge (P23) - aware non-users, n≈200	3,561	0.163	-	Not confirmed
Sat.	P13 satisfaction - active users, n=495	16,168	0.984	-	No difference

Note. * $p<0.05$. Direction refers to higher mean score on the ordinal scale. Speed surcharge subsamples exclude non-users. Nagelkerke R2=0.044

Source: own elaboration

Table 5. **Ordinal regression - OS coefficient (iOS vs. Android) across models**

Model	Sample	β (iOS)	SE	t	p
H1 - WTP delivery	Active users (n≈491)	0.411	0.230	1.784	0.074
H1 - WTP delivery	Aware non-users (n≈418)	−0.120	0.264	−0.454	0.650

H2 - Speed surcharge	Active users (n≈465)	−0.534	0.256	−2.089	0.037
H2 - Speed surcharge	Aware non-users (n≈200)	0.726	0.425	1.708	0.088
Satisfaction (P13)	Active users (n≈491)	-	-	-	0.984
H3 - OS × income (LR test)	Active users (n≈491)	-	-	χ^2=1.54	0.820

Note. All models control for age, education, income, and settlement size. H3 row: likelihood ratio test for OS × income interaction term.

Source: own elaboration

5. Discussion

5.1 Device-based segmentation offers no reliable signal in q-commerce

The results suggest that OS may not function as a reliable predictor of willingness to pay in the Polish q-commerce market. In both groups, the results give more support to the absence of a clear effect than to the presence of one, but in the active-user model the estimated iOS effect is still positive. Its confidence interval shows that a small or moderate positive effect cannot be fully ruled out.

H3 adds an important constraint on interpretation. The income distribution across OS groups is statistically indistinguishable (χ^2=2.98, p=0.562), which rules out income confounding as an explanation for the null result on H1. If the wealth selection mechanism were active, some income difference should be detectable - it is not. This shifts attention toward contextual factors specific to the service type. The limited predictive validity of OS as a segmentation variable appears not to be specific to q-commerce. Ungerer and Gumbinger (2024), in a US survey sample (N=195), found that smartphone OS did not predict daily health habits after controlling for age and income - suggesting that OS may be a weak behavioural predictor across multiple domains once sociodemographic factors are held constant.

The mechanism behind the strongest evidence for OS-based spending differentiation - the ecosystem-habituation effect documented by Ghose and Han (2014, Section 2.1) - sits in a specific context: discretionary purchases (digital games, subscriptions, in-app content) embedded in platform ecosystems. In these categories, device value plausibly signals purchasing power, and ecosystem habituation lowers the psychological cost of spending. Quick commerce does not satisfy these conditions. The purchase responds to an unplanned need, the product is undifferentiated, and the relevant reference price is not a competing application but a physical store within walking distance. This mechanism belongs to the discretionary, platform-embedded transaction type - there is no reason to expect it to carry over to a necessity-driven service context.

The status-signalling mechanism documented by Bursztyn et al. (2025) - where iPhone owners actively protect their social identity and associate green-bubble messaging with negative social judgement - is consistent with OS differences in discretionary, identity-expressive contexts. A delivery fee payment, however, is not a social act: it is invisible to peers and carries no affiliation signal. Under such conditions the signalling premium that makes OS a reliable predictor of willingness to pay in the app market has no channel through which to operate.

The functional character of q-commerce may account for this pattern. Unlike app purchases - which are discretionary, identity-expressive, and embedded in platform ecosystems - grocery delivery is primarily a convenience service addressing an immediate practical need. Wakefield and Inman (2003) show that price sensitivity is systematically lower for hedonic than for utilitarian consumption occasions, and that income moderates this effect primarily in hedonic contexts. In a necessity-driven setting, consumers may evaluate delivery fees more instrumentally and with less reference to symbolic or ecosystem-related considerations. Under such conditions, the behavioural distinctions associated with smartphone operating systems may lose predictive power.

The apparent ambiguity noted in Section 2.2 resolves once q-commerce is decomposed into its two priced components. The delivered good is functional - the standard delivery fee that gets it there is loss-coded against the zero-cost physical-retail baseline, exactly as H1 assumes. Speed itself is a different purchase: paying to compress a fixed wait into fifteen minutes is a discretionary upgrade, closer to a hedonic indulgence than a functional necessity. H1 and H2 therefore test willingness to pay for two objects with different psychological status, not two measurements of the same underlying construct.

This decomposition motivates a closer look at the reversed H2 effect in the next section.

5.2. The reversed H2 effect: how q-commerce users relate to speed

The significant OS effect on speed surcharge tolerance ($\beta=-0.534$, $p=0.037$) ran directly counter to H2. Android users showed higher WTP for faster delivery than iOS users. This result survives full demographic controls and is not attributable to the age or settlement size differences observed between OS groups.

The younger and more urban profile of iOS users suggested that settlement size might account for the reversal. iOS users are overrepresented in the largest cities, where q-commerce delivery speeds are already high and a speed surcharge may feel redundant; Android users, more evenly distributed across smaller cities, may face greater variation in baseline speed. A likelihood ratio test on the OS × settlement size interaction yielded $\chi^2=0.91$ (df=3, p=0.823). Settlement size does not moderate the effect.

Speed is a service-defining attribute in q-commerce, not a discretionary add-on - the interpurchase-time findings of Harter et al. (2025, Section 2.2) point the same way. If speed deviations have measurable consequences for retention, the asymmetric willingness to pay a surcharge observed here may reflect consumers' internalised awareness of this cost, independently of their device type.

Differential order frequency and basket urgency offer two candidate explanations. Less frequent users may assign higher subjective value to each delivery, increasing WTP for speed when they do order; users ordering for immediate consumption face a higher time cost of waiting than those doing planned restocking. Both mechanisms predict higher Android WTP without requiring any income difference - that fits the H3 result, though direct measurement of order frequency and basket composition was not part of the study design.

5.3. When does device-based segmentation work - and when does it fail?

H3's confirmation rules out one explanation for the null result on H1. The wealth selection mechanism alone cannot account for it. The empirical case for iOS as a reliable income signal was built on evidence from app markets where Android's flagship segment was substantially smaller and functional differentiation between platforms more pronounced. As Android increasingly spans the full device price spectrum - encompassing both budget and flagship devices at equivalent price points - the OS category may become too heterogeneous to carry the wealth-selection signal on which device-based segmentation depends. In Poland, where iOS accounts for approximately 12% of smartphones (IQS, 2025), high-income consumers appear on both sides of the OS divide. Under these structural conditions, device value may be the more appropriate segmentation construct. That said, this is a hypothesis for future research, not a finding of this study.

General e-commerce sensitivity to delivery fees is already substantial (Gosling et al., 2025, Section 1.2). If a comparable sensitivity is even partially reproduced in Poland - where physical retail offers a near-zero-cost alternative - the WTP variance captured here may represent the ceiling of what any single segmentation variable, including OS, can reliably detect.

The conditions under which device-based segmentation is likely to fail or hold can be stated across three structural axes. Together, they identify the scope conditions of the OS-as-proxy mechanism rather than treating the null result as a blanket rejection.

Table 6. **Boundary conditions for OS-based consumer segmentation**

Axis	Conditions as in this study → no OS effect expected	Contrasting conditions → OS effect expected
Industry / service type	Necessity goods and functional delivery services (grocery q-commerce): purchase triggered by immediate need, undifferentiated product, price evaluated against a physical alternative	Discretionary, identity-expressive categories (premium apps, gaming, luxury subscriptions): platform habituation and status considerations active
Country - retail density	High physical retail density, as documented for Poland (Section 1.1): zero-cost substitution alternative within walking distance compresses WTP variance across device segments	Lower physical retail density: no comparable zero-cost alternative; online becomes the default channel, preserving cross-segment WTP differentiation
Country - Android price spectrum	Broad Android device price range, iOS/Android price distributions overlapping - confirmed empirically via the null OS-income association reported in Section 4.1	Android concentrated in the budget tier, iOS/Android price distributions clearly separated (as in Ghose & Han, 2014; Bursztyn et al., 2025): OS retains income-proxy validity

Source: own elaboration

The three axes carry different evidentiary weight in this study. The Android price-spectrum axis is confirmed directly: the null OS-income association reported in Section 4.1 is the observable signature of overlapping price distributions, not an assumption imported from elsewhere. The retail-density axis is a documented contextual fact about Poland (Section 1.1), but untested against a comparison market within this design. The service-type axis is motivated by the literature reviewed in Section 2.1, but this study examines only one service category. The null result on H1 is therefore consistent with the confirmed price-spectrum overlap, but retail density and service type remain candidate contributors that country- and industry-level replication would need to isolate.

The replications proposed below separate service type from country structure, but not the two country-level axes from each other. A structurally similar study conducted in the US or Canada would test the country-level axes jointly: both markets combine lower retail density with a more budget-concentrated Android segment, relative to Poland. A positive iOS effect there, conditional on income controls, would confirm that country structure matters, without revealing which of the two country-level axes carries the weight.

A cross-industry replication within Poland isolates service type instead, holding country structure fixed. Food delivery, ride-hailing, and digital subscriptions offer a useful contrast. If OS predicts WTP for digital subscriptions but not for grocery delivery in the same Polish sample, service type is the operative boundary condition, independent of country context.

A multi-country replication across Czechia, Hungary, and Romania would test whether Poland's null result generalises across the region, or depends on its particular combination of retail density and device market structure. This study provides direct evidence only for Poland.

5.4. Managerial implications

The findings carry several practical implications for q-commerce operators. The most direct is negative: the present data do not support using operating system as a proxy for willingness to pay when setting delivery fees in the Polish market. The data provide no empirical basis for charging iOS users more, or for assuming that they will absorb higher fees more readily than Android users. OS and declared income are statistically independent in this sample, which rules out the simplest justification for device-based pricing - the assumption that iOS users possess greater purchasing power and therefore tolerate higher delivery fees. The iOS premium was not confirmed. That alone should give operators pause before charging iOS users more. But it points to something broader: the logic of using device type as an income proxy deserves scrutiny in any market where Android spans the full device price spectrum.

Behavioural variables already collected through platform operations - order frequency, basket composition, purchase history - are more direct proxies for engagement and spending capacity than device metadata. Whether they outperform OS as WTP predictors is a question this data cannot answer directly. The structural limitations identified above, though, point in that direction. OS may retain value in content strategy and UX personalisation, where ecosystem differences between iOS and Android users are better established and do not require income-based inference.

6. Conclusions

This study does not support mobile operating system as a reliable standalone predictor of willingness to pay in Polish q-commerce. H1 was not supported in either group. Among active users, the observed odds ratio is directionally consistent with the hypothesis, but the study was underpowered to detect small effects, so this result should be interpreted as statistically inconclusive rather than as evidence of no effect. The only statistically significant OS effect concerns willingness to pay a speed surcharge and runs counter to the hypothesis: Android users show higher willingness to pay for faster delivery than iOS users, driven by a higher share of respondents reporting unconditional willingness to pay. This reversal fits the reference-point framework introduced in Section 2. A speed surcharge is framed as the price of a benefit, not an unavoidable loss. And delivery fee payment carries none of the social visibility that gives OS its signalling premium in discretionary markets.

The findings are consistent with the view that OS may be a structurally weak income proxy in markets where Android spans the full device price spectrum. With iOS accounting for only 12% of the Polish smartphone market, the Android category in Poland encompasses both budget and flagship devices, which may dilute the wealth-selection signal that underpins device-based segmentation in higher-penetration markets. Whether this structural argument extends to other CEE markets with similar OS distributions remains an empirical question beyond the scope of the present study.

This study shows that findings from app market and subscription research do not transfer automatically to q-commerce contexts, and that the predictive validity of OS as a segmentation variable is conditional on market structure and service type - the boundary conditions for which are detailed in Section 5.3 (Table 6).

The predictive mechanisms established in app-market research - wealth selection, ecosystem habituation, status signalling - did not transfer to q-commerce as anticipated. OS showed no reliable positive effect on willingness to pay for either fee type, and where a significant effect did emerge, it ran opposite to prediction. Device-based segmentation calibrated on discretionary digital purchases does not appear to generalise to a loss-framed, necessity-driven service context.

In markets where Android spans the full device price spectrum, the wealth-selection signal underlying device-based segmentation appears structurally weaker. Device value - smartphone price tier as a more direct operationalisation of spending capacity - should be tested as a potentially more appropriate segmentation construct, though the present data do not permit this comparison directly.

OS does not have empirical support as a basis for delivery fee differentiation in the Polish market, and the present data provide no basis for assuming iOS users will absorb higher fees more readily than Android users. Behavioural variables from transaction data are more direct proxies for spending capacity and should be prioritised for pricing segmentation over device metadata. OS may retain limited utility in UX personalisation, where ecosystem differences are better established.

The most substantive limitation is the absence of device value data: smartphone price tier is a more direct operationalisation of the wealth-selection mechanism than operating system, and its omission means the null result on H1 cannot be attributed to a weak mechanism or a weak proxy. The interpretation of the reversed H2 effect is similarly constrained - without behavioural and contextual data collected at the moment of ordering, the source of the Android speed surcharge premium cannot be identified.

Finally, the cross-sectional design precludes any assessment of whether these patterns are stable over time, which matters in a segment where consumer behaviour is still adjusting to a relatively new service format. Poland's exceptional retail density, while making it a diagnostic setting for the reference-point mechanism, also means the null result cannot be cleanly separated from this specific market condition; the boundary-conditions framework in Section 5.3 identifies retail density as one of two axes this design cannot isolate.

The boundary conditions under which this transfer might hold are detailed in Section 5.3 (Table 6). Future research should test these predictions directly: replication in markets with lower physical retail density, a narrower Android price spectrum, or in discretionary rather than necessity-driven service categories would each isolate a different boundary condition rather than treating the present null result as a blanket rejection of device-based segmentation.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used Claude (Anthropic) in order to improve the readability and linguistic quality of the manuscript. After using this tool/service, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

bolttech Poland. (2025, April 8). Ma maksymalnie 1,5 roku, kosztuje ponad 1 000 zł i nie ma rodzeństwa. Co wiemy o smartfonie statystycznego Polaka? [It's no more than 1.5 years old, costs over PLN 1,000 and has no siblings. What do we know about the average Polish smartphone?]. https://38pr.prowly.com/396597-ma-maksymalnie-15-roku-kosztuje-ponad-1-000-zl-i-nie-ma-rodzenstwa-co-wiemy-o-smartfonie-statystycznego-polaka

Brant, R. (1990). Assessing Proportionality in the Proportional Odds Model for Ordinal Logistic Regression. *Biometrics, 46*(4), 1171–1178. https://doi.org/10.2307/2532457

Bursztyn, L., Jiménez-Durán, R., Leonard, A., Milojević, F., & Roth, C. (2025). Non-user utility and market power: The case of smartphones (*NBER Working Paper No. 33642)*. National Bureau of Economic Research. https://doi.org/10.3386/w33642

Ghose, A., & Han, S. P. (2014). Estimating Demand for Mobile Applications in the New Economy. *Management Science, 60*(6), 1470–1488. https://doi.org/10.1287/mnsc.2014.1945

Gosling, S., Pan, I., Li, L., & Shenoy, S. (2025, February 13). *What do US consumers want from e-commerce deliveries?*. McKinsey & Company. https://www.mckinsey.com/industries/logistics/our-insights/what-do-us-consumers-want-from-e-commerce-deliveries

Götz, F. M., Stieger, S., & Reips, U.-D. (2017). Users of the main smartphone operating systems (iOS, Android) differ only little in personality. *PLOS ONE, 12*(5), e0176921. https://doi.org/10.1371/journal.pone.0176921

Hannak, A., Soeller, G., Lazer, D. M. J., Mislove, A., & Wilson, C. (2014). Measuring price discrimination and steering on e-commerce web sites. In *Proceedings of the 2014 Conference on Internet Measurement Conference* (pp. 305–318). Association for Computing Machinery. https://doi.org/10.1145/ 2663716.2663744

Harter, A., Stich, L., & Spann, M. (2025). The Effect of Delivery Time on Repurchase Behavior in Quick Commerce. *Journal of Service Research, 2*8(2), 211–227. https://doi.org/10.1177/10946705241236961

International Data Corporation. (2025, February 25). *Worldwide smartphone market forecast to grow 2.3% in 2025, led by Android growth in China and U.S., amid 10% China tariffs, according to IDC.* https://my.idc.com/ getdoc.jsp?containerId=prAP53217825

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica, 47*(2), 263. https://doi.org/10.2307/1914185

Keusch, F., Bähr, S., Haas, G.-C., Kreuter, F., & Trappmann, M. (2023). Coverage Error in Data Collection Combining Mobile Surveys With Passive Measurement Using Apps: Data From a German National Survey. *Sociological Methods & Research, 52*(2), 841–878. https://doi.org/10.1177/0049124120914924

Kooti, F., Grbovic, M., Aiello, L. M., Bax, E., & Lerman, K. (2017). iPhone's digital marketplace: Characterizing the big spenders. In *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining* (pp. 13–21). Association for Computing Machinery. https://doi.org/10.1145/3018661.3018697

Kułyk, P., & Michałowska, M. (2016). Consumer behaviour on the e-commerce market in the light of empirical research in Lubuskie voivodeship. *Management, 20*(1), 239–255. https://doi.org/10.1515/manment-2015-0037

Łagutko, T. (2025). Q-commerce w Polsce – model konceptualny funkcjonowania ultraszybkich dostaw w warunkach wysokiej konkurencji detalicznej. [Q-commerce in Poland – a conceptual model of ultra-fast delivery operations in a highly competitive retail environment]. *Ekonomika i Organizacja Logistyki, 10*(2), 35–46. https://doi.org/10.22630/EIOL.2025.10.2.10

Liu, A., He, H., Tu, X. M., & Tang, W. (2023). On testing proportional odds assumptions for proportional odds models. *General Psychiatry, 36*(3), e101048. https://doi.org/10.1136/gpsych-2023-101048

Moore, J. C., Stinson, L. L., & Welniak, E. J., Jr. (2000). Income measurement error in surveys: A review. *Journal of Official Statistics, 16*(4), 331–361.

Nguyen, D. H., De Leeuw, S., Dullaert, W., & Foubert, B. P. J. (2019). What Is the Right Delivery Option for You? Consumer Preferences for Delivery Attributes in Online Retailing. *Journal of Business Logistics, 40*(4), 299–321. https://doi.org/10.1111/jbl.12210

Thaler, R. (1985). Mental Accounting and Consumer Choice. *Marketing Science, 4*(3), 199–214. https://doi.org/ 10.1287/mksc.4.3.199

The Business Research Company. (2026). *Quick Commerce market size, share, trends analysis report 2026.* https://www.thebusinessresearchcompany.com/report/quick-commerce-global-market-report

Tourangeau, R., & Yan, T. (2007). Sensitive questions in surveys. *Psychological Bulletin, 133*(5), 859–883. https://doi.org/10.1037/0033-2909.133.5.859

Ucar, I., Gramaglia, M., Fiore, M., Smoreda, Z., & Moro, E. (2021). News or social media? Socio--economic divide of mobile service consumption. *Journal of The Royal Society Interface, 18*(185), 20210350. https://doi.org/ 10.1098/rsif.2021.0350

Ünal, P., Temizel, T. T., & Erhan Eren, P. (2015). A Study on User Perception of Mobile Commerce for Android and iOS Device Users. In M. Younas, I. Awan, & M. Mecella (Eds.), *Mobile Web and Intelligent Information Systems* (Vol. 9228, pp. 63–73). Springer International Publishing. https://doi.org/10.1007/978-3-319-23144-0_6

Ungerer, M. N., & Gumbinger, C. (2024). A Comparative Survey on Daily Health Habits Among iPhone and Android Smartphone Users. *American Journal of Lifestyle Medicine,* 15598276241268195. https://doi.org/ 10.1177/15598276241268195

Van Droogenbroeck, E., & Van Hove, L. (2022). Are the Time-Poor Willing to Pay More for Online Grocery Services? When 'No' Means 'Yes.' *Journal of Theoretical and Applied Electronic Commerce Research, 17*(1), 253–290. https://doi.org/10.3390/jtaer17010013

Wakefield, K. L., & Inman, J. J. (2003). Situational price sensitivity: The role of consumption occasion, social context and income. *Journal of Retailing, 79*(4), 199–212. https://doi.org/10.1016/j.jretai.2003.09.004