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Mobile–Desktop Channel-Mix Divergence in Lithuanian E-Commerce: Evidence from 500 Sites, 2022–2025

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Abstract: *Using SimilarWeb estimates for 500 Lithuanian e-commerce websites sampled across randomly drawn months in the period January 2022 to December 2025 (N = 14,443 site-months), this paper documents systematic divergence between the acquisition-channel mix on mobile and desktop devices within the same sites. Compared with their desktop counterparts, mobile sessions draw a substantially smaller share from direct traffic (20.6% vs 35.6%, Δ = −15 percentage points, Cohen d = −0.85) and a much larger share from social referrals (10.5% vs 3.2%, Δ = +7.3 pp, d = 0.47) and organic search (45.9% vs 39.5%, Δ = +6.4 pp, d = 0.26). Paid channels are only marginally smaller on mobile, contrary to the common practitioner assumption that mobile traffic is more paid-dependent. A cross-site OLS regression with heteroskedasticity-robust standard errors confirms that a one-point increase in mobile intensity is associated with a 32-point drop in the direct-traffic share and a 10-point rise in the social share. The findings indicate that device–channel interactions are a first-order feature of small-economy e-commerce traffic and should be incorporated into both attribution modelling and marketing-mix planning.*
Keywords: *mobile commerce, traffic acquisition, channel mix, SimilarWeb, Lithuania, e-commerce, attribution.*

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I. INTRODUCTION

Mobile devices now generate the majority of e-commerce visits in most European markets, yet academic and practitioner discussions of "channel mix" still often treat a website as a single acquisition funnel. This conflation is problematic because the set of channels available on a smartphone (in-app social links, voice or app-driven search) differs meaningfully from the desktop set (bookmarks, browser history, type-in URLs). If the device shifts users to a different mix of acquisition channels, attribution models calibrated on desktop behaviour will systematically mis-price paid campaigns aimed at mobile audiences, and vice versa.

This paper uses a large panel of SimilarWeb traffic estimates for Lithuanian e-commerce websites to ask one question: conditional on the same site in the same month, how different is the acquisition channel mix on mobile compared with desktop? The Lithuanian market is a useful case because it is small enough to cover almost its entire e-commerce long tail (500 sites) yet developed enough to include mature retail brands alongside pure marketplaces. We document sizeable and statistically robust divergence, with magnitudes that should interest both researchers studying platform effects on consumer navigation and practitioners allocating media budgets across devices.

II. DATA

We use SimilarWeb monthly traffic estimates covering 500 Lithuanian e-commerce websites, with randomly sampled months drawn from the 48-month window January 2022 to December 2025. The exported dataset contains 15,137 site-month observations across seven acquisition channels — direct, organic search, paid search, paid display, social, email and referrals — separately for total and mobile traffic. After dropping zero-visit observations and restricting to sites with strictly positive visits on both platforms, the final sample contains 14,443 site-months. The mobile share of total visits averages 60.0% (median 61.9%, SD 18.4%), confirming that mobile dominates Lithuanian e-commerce volume.

For every channel c and observation i we compute two shares: the mobile-only share $m_{io} = M_{io}$ / mobile-visits$_i$ and the desktop-only share $d_{io} = (\text{Total}_{io} - M_{io})$ / desktop-visits$_i$. Because each observation is its own control, the paired mobile–desktop contrast is immune to unobserved site-level confounders such as brand strength, assortment width or category. We also compute total channel shares to study how site-level mobile intensity correlates with the overall acquisition mix.

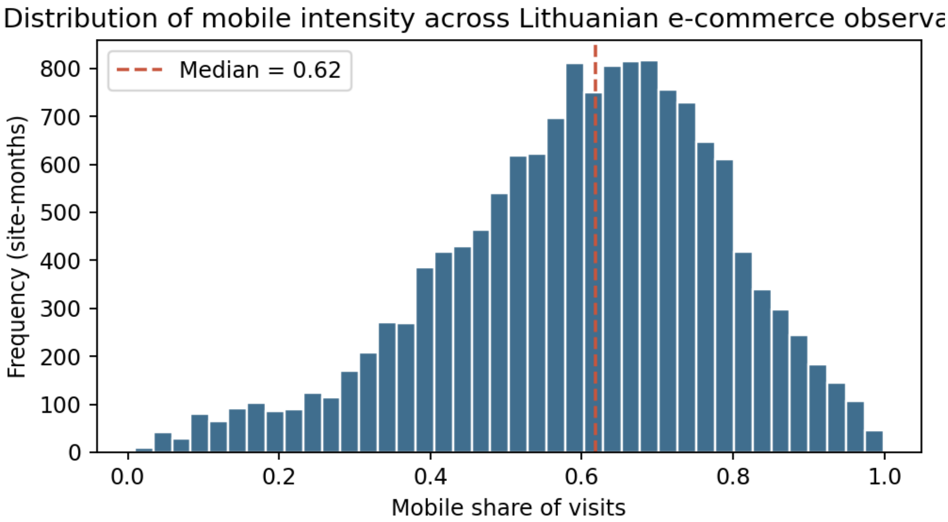

Figure 1. Distribution of mobile share of visits across Lithuanian e-commerce site-months (N = 14,443). The median site-month receives 61% of its visits on mobile, with substantial heterogeneity (interquartile range 47–74%).

III. METHOD

Three complementary analyses are reported. First, a paired within-site comparison of mobile vs desktop shares for each channel, with Wilcoxon signed-rank tests and Cohen's d as the effect-size metric. Second, Pearson and Spearman correlations between site-level mobile intensity and each total channel share, Bonferroni-corrected at 0.05/7. Third, ordinary least squares with heteroskedasticity-robust (HC1) standard errors regressing each total channel share on the mobile intensity variable. All calculations were performed in Python 3.11 using pandas 2.1, NumPy 1.26, SciPy 1.11 and statsmodels 0.14.

IV. RESULTS

4.1 Within-site mobile–desktop channel-mix gaps

Table 1 shows that all seven channels display significantly different shares on mobile compared with desktop (all Wilcoxon $p < 0.001$), but with sharply different magnitudes and directions. The largest shift is in direct traffic: the average desktop-only share is 35.6%, versus only 20.6% on mobile — a 15-point gap and a large effect size (paired Cohen $d = -0.85$). Social traffic moves the opposite way, from 3.2% on desktop to 10.5% on mobile (+7.3 pp, $d = 0.47$). Organic search is also more salient on mobile (+6.4 pp, $d = 0.26$), while paid search is slightly smaller on mobile (−2.0 pp). Paid display, email and referrals move in the same direction as paid search but with very small magnitudes.

Channel	N	Desktop mean %	Desktop med %	Mobile mean %	Mobile med %	Δ mean (pp)	Cohen d	Wilcoxon p
Direct	14,443	35.63	32.86	20.63	18.84	-15.00	-0.846	<0.001
OrganicSearch	14,443	39.50	36.57	45.87	48.86	+6.37	0.256	<0.001
PaidSearch	14,443	10.68	7.17	8.70	0.00	-1.98	-0.114	<0.001
PaidDisplay	14,443	2.00	0.03	1.90	0.03	-0.10	-0.013	<0.001
Social	14,443	3.16	1.48	10.45	4.10	+7.29	0.468	<0.001
Mail	14,443	1.60	0.00	1.62	0.00	+0.02	0.002	<0.001
Referrals	14,443	6.22	2.06	4.15	1.74	-2.07	-0.206	<0.001

Table 1. Channel shares within-observation: mobile vs desktop. Shares are within-platform (channel / platform visits). Wilcoxon p-values are paired, two-sided. All channels differ significantly at $p < 0.001$; direct and social show large effect sizes.

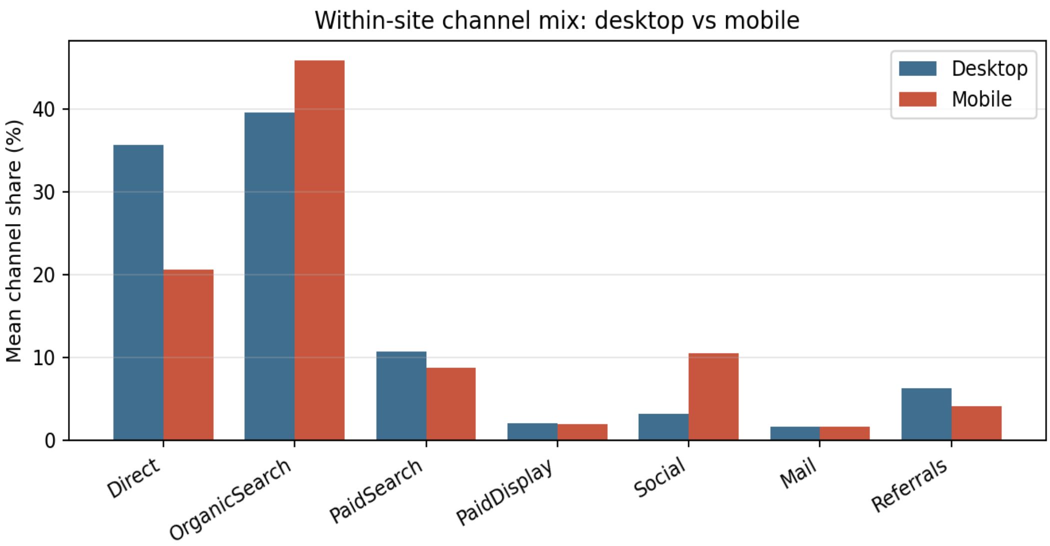

Figure 2. Mean within-platform channel shares: desktop versus mobile. The collapse of direct traffic and the rise of social traffic on mobile are the two dominant features of the Lithuanian channel-mix shift.

4.2 Correlation of mobile intensity with total channel composition

Table 2 reports OLS coefficients from regressing each total channel share on mobile intensity. A one-unit increase in mobile share is associated with a 32-point drop in direct share ($p < 0.001$) and a 10-point rise in social share ($p < 0.001$). Organic-search share does not vary systematically with mobile intensity ($p = 0.07$): sites with more mobile traffic are not more organic-driven in absolute terms, but they rely relatively more on organic within the mobile mix. Paid search and paid display shares rise slightly with mobile intensity (+6.5 pp and +1.6 pp respectively), while referrals fall by 3.8 pp.

Dep. var: channel share	Intercept	β mobile share	SE	t	R^2	N
Direct	0.460	-0.320	0.010	-33.25	0.124	14,443
OrganicSearch	0.414	0.022	0.012	1.84	0.000	14,443
PaidSearch	0.055	0.065	0.006	10.38	0.008	14,443
PaidDisplay	0.009	0.016	0.002	7.03	0.004	14,443
Social	0.016	0.101	0.005	20.98	0.028	14,443
Mail	0.015	0.001	0.002	0.35	0.000	14,443
Referrals	0.073	-0.038	0.004	-9.30	0.007	14,443

Table 2. Pooled OLS with HC1 robust standard errors: each total channel share regressed on mobile share (0–1). All p-values < 0.001 except organic search (p = 0.07) and mail (p = 0.72).

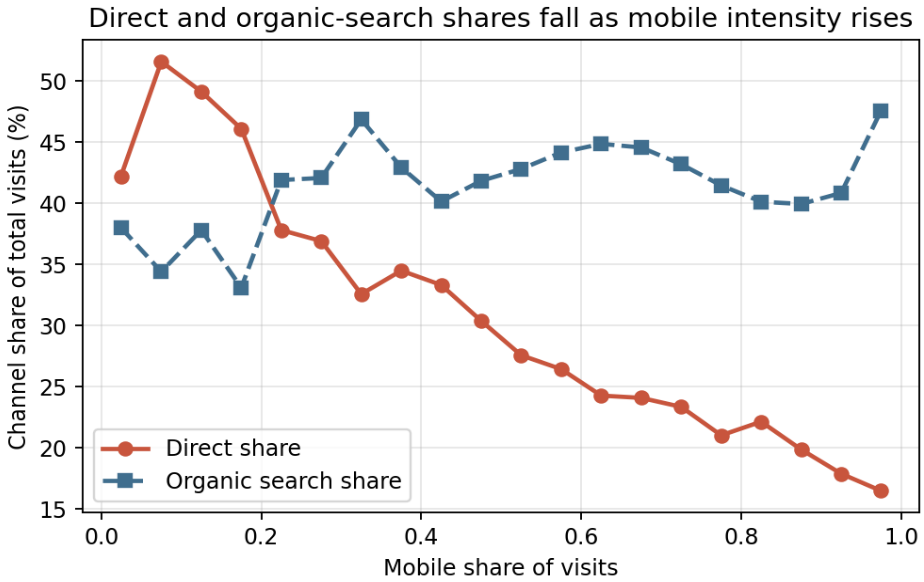

Figure 3. Binned means of direct share and organic-search share against mobile share of visits. Direct falls monotonically as mobile intensity rises; organic search is essentially flat.

V. DISCUSSION

Three findings stand out. First, direct traffic is disproportionately a desktop phenomenon in the Lithuanian e-commerce market. The collapse from 35% to 21% within the same sites is consistent with the disappearance of URL-bar typing and browser bookmarks as navigation tools on smartphones, and with users returning to known retailers through push notifications, saved apps and social posts rather than by typing the domain. Second, social traffic is largely a mobile phenomenon: roughly three-quarters of all social visits to these sites occur on mobile, and social is the single channel that sees its share more than triple when moving from desktop to mobile. Third, contrary to a common practitioner claim that mobile traffic is more paid-dependent, paid search and paid display shares are in fact slightly smaller on mobile than on desktop in our data. Paid media is not the main substitute for lost direct traffic on mobile; social is.

These patterns have immediate implications. Attribution models that treat mobile and desktop as interchangeable will systematically over-credit direct traffic as an "earned" outcome of brand investment on mobile, because direct is suppressed there for reasons that have nothing to do with brand strength. Conversely, they will under-credit the upstream role of social content in acquiring mobile visitors. Marketing-mix planning that holds device-weighted budgets constant will therefore misallocate spend toward direct-equivalent channels (such as email remarketing) and away from social.

Three limitations should be noted. The data are SimilarWeb panel-based estimates rather than first-party analytics, so absolute shares will differ from any individual site's GA4 figures; however, the within-site contrast is less sensitive to scale noise and should remain directionally accurate. The exported dataset does not carry explicit site identifiers, so results are reported as pooled cross-sectional associations rather than within-site fixed-effects; reversing this in follow-up work would improve the causal interpretation of the device–channel gradient. Finally, the Lithuanian market is small and dominated by a handful of large retailers and marketplaces, so generalisation to very different markets (e.g. the United States) should be done cautiously.

VI. IMPLICATIONS FOR MARKETERS, MEDIA PLANNERS AND CEOS

6.1 For CEOs and boards

Direct traffic is conventionally treated as a board-level proxy for brand strength: the more customers type your URL or open their bookmark, the stronger the brand. The data here show that this interpretation breaks down on mobile. The same Lithuanian e-commerce websites receive, on average, only 21% of their mobile visits through direct versus 36% on desktop — a gap driven by the smartphone interface rather than by brand erosion. Boards that rely on a single direct-traffic key-performance-indicator (KPI) will therefore systematically under-estimate the brand health of mobile-heavy businesses (typically consumer-goods, fashion and grocery retailers) and over-estimate it for desktop-heavy ones (typically B2B, office-supply and travel). A practical recommendation is to report direct share separately for each device and to track changes within device over time, rather than across devices at a point in time.

6.2 For media planners and performance teams

Attribution and media-mix models calibrated on desktop data will mis-price three channel groups. First, direct traffic credits will be inflated on desktop and suppressed on mobile, causing remarketing and customer-relationship-management (CRM) budgets to be under-funded on smartphones. Second, social traffic, which triples in share from desktop to mobile, is routinely under-credited in last-click attribution because it sits upstream of a paid-search or direct click. Planners should adopt device-specific attribution weights and consider multi-touch models that explicitly account for social-first, mobile-dominant journeys. Third, the common practitioner assumption that "mobile equals paid" is not supported in this dataset: paid shares are slightly lower on mobile, so reallocating mobile budget from paid to social-content production is likely to improve cost per acquisition for most retailers.

6.3 For marketers

Three operational priorities follow. First, treat mobile and desktop as separate acquisition funnels with separate channel strategies — not as a single funnel with a 'mobile responsive' skin. Second, invest in social-commerce infrastructure (shoppable posts, Reels, TikTok Shop, creator partnerships) as the mobile substitute for lost direct traffic. Our data imply that every 10-point rise in mobile intensity is associated with roughly a 1-point rise in social share — small in average but concentrated among the fastest-growing retailers. Third, build repeat-visit mechanisms native to mobile (progressive web apps, push notifications, loyalty-app engagement) to rebuild a mobile equivalent of the 'direct' relationship that smartphones suppress.

VII. CONCLUSION

Within the same Lithuanian e-commerce websites, mobile and desktop deliver very different channel mixes. Mobile traffic is less direct, less referral-driven and more social, with only minor shifts in paid media. The device–channel interaction is large enough (effect sizes up to $d = 0.85$) to justify treating mobile and desktop as separate acquisition funnels in both academic research and practitioner attribution models. Future work should access first-party, identified panels to allow within-site fixed-effect estimation and to test whether the magnitudes documented for Lithuania generalise to other small European e-commerce economies.

VIII. ACKNOWLEDGEMENTS

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