

Harnessing friction topology for stage-sensitive checkout diagnostics in supplement e-commerce

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Abstract. *This study examined checkout disruption in supplement e-commerce using aggregated Google Analytics 4 (GA4) funnel exports from an established supplement brand. The purpose was to develop and test friction topology, a stage-sensitive diagnostic model that locates checkout losses across five funnel stages by device category and first user medium. Transition-loss vectors were computed for overall, device-based and medium-based contexts. The dominant friction peak occurred before cart entry, while device and medium differences emerged after cart entry, at the shipping, payment and purchase stages. The main contribution is a diagnostic model applicable to aggregated GA4 data, without individual user tracking.*

Keywords. Friction topology, GA4, checkout funnel, supplement e-commerce, user progression, device category, first user medium

1 Introduction

Checkout loss has become a major practical and theoretical challenge in digital commerce. Traffic acquisition costs are rising, while privacy regulations and platform measurement limits reduce visibility into user pathways. In practice, Google Analytics 4 (GA4) funnel reports in this context are usually reviewed as static tables during weekly performance meetings, with limited discussion of where exactly users drop out of checkout. In supplement e-commerce, this is compounded by product evaluation, health assurances, delivery expectations and payment trust. The supplement sector was selected as the research context because supplements are credence goods, where trust and reassurance matter at every stage of the checkout process. The sector combines health-related risk perception with routine online retail mechanics, which makes stage-specific friction more pronounced than in low-involvement categories. Funnel-level diagnostics in this sector also remain under-researched compared

to fashion or electronics e-commerce. Users may therefore abandon their purchase before reaching the cart, when relevance is not established, or after entering the cart, when interaction costs become too high. Recent work on clickstream analysis, checkout simplification and cart abandonment shows that observed behaviour can reveal purchase disruptions hidden by final conversion rates (Jabr et al., 2023; Kukar-Kinney et al., 2022; Unal & Park, 2023).

Current funnel analytics do not fully address this issue. GA4 Funnel Exploration can show user retention or attrition across predefined stages. Still, its output is usually read as a descriptive report of drop-off rates rather than a structured behavioural model (Google, 2026b). Survey-based models of acceptance, risk and effort explain why users hesitate, but link less directly to the consolidated funnel exports used in day-to-day management (Chopra et al., 2024; Liu & Mensah, 2024; Roy & Shaikh, 2024). A gap exists between behavioural theory and routine analytics practice: the order, position and context of checkout loss are rarely preserved in a concise model for aggregated GA4 data.

This paper aimed to develop and assess friction topology as a stage-sensitive diagnostic model for checkout. Friction was treated not as an isolated factor but as a transition-level quantity from which topology is estimated. The hypotheses were that checkout loss would not be evenly distributed across the funnel, and that device category and first user medium would create distinct topological patterns once users had signalled intent by entering the cart. The analysis focused on a well-known supplement e-commerce brand, using GA4 data segmented by device and medium. The remainder of this paper is organised as follows: Section 2 presents a structured literature review and the development of hypotheses. Section 3 describes GA4 data, stage definitions and formulas. Section 4 presents the overall, device-based, and medium-based results. Section 5 discusses scientific contribution, managerial implications and limitations. Section 6 summarises the achieved contribution and presents future research directions.

2 Literature Review and Hypotheses

2.1 Structured review logic

Four concepts are used throughout this paper. A friction point is a single transition between two adjacent funnel stages at which users abandon the purchase path. Transition friction is the share of users who do not progress through a given friction point (formally defined in Section 3.2). A friction topology is the ordered vector of transition-friction values across all checkout stages for a given context; it describes how loss is distributed along the funnel rather than only how large it is in total. A friction peak is the transition with the highest friction value within a topology vector. A medium-friction topology (or device-friction topology) is the friction topology computed separately for each first user medium or device category.

The literature was screened to establish a basic framework before empirical analysis. Recent academic articles were reviewed across four interconnected domains: clickstream and journey modelling, cart abandonment, mobile and interface effort, and omnichannel acquisition contexts. Priority was given to studies examining behaviour, transition effort, perceived risk, or the structure of online journeys. The review aimed to support theory development and hypothesis formulation rather than to serve as a full systematic literature review. Clickstream and journey studies show that behaviour can be traced into interpretable models of online progression. Jabr et al. (2023) modelled revisiting and purchasing using clickstream data; Kim et al. (2024) incorporated browsing patterns into purchase prediction; and Padilla et al. (2025) approached the customer journey as a source of information under first-party data constraints. These studies support the view that meaningful information is contained in sequences and stages and not only at the final purchase event.

Cart abandonment studies were retained because checkout loss is multi-causal. In recent work, abandonment has been linked to search and comparison, risk perception, online review confusion, cognitive load, choice variety, and device conditions (Chopra et al., 2024; Das Sarma et al., 2025; Kukar-Kinney et al., 2022; Roy & Shaikh, 2024). This stream supports the assumption that an identical abandonment rate can have varying implications depending on the stage at which it occurs. Mobile commerce, online experience, and omnichannel studies were retained since context may alter the task the user is performing. Device differences can affect ease of interaction and form completion (Almeida Lucas et al., 2023), while acquisition context can shift expectation alignment, confidence and readiness to proceed (Fang & Li, 2025; Koronaki et al., 2023; Moliner & Tortosa-Edo, 2024). Therefore, a diagnostic model should preserve not only the amount of loss, but also its location and segment context.

2.2 Research gap and hypotheses

Two gaps can be identified in the retained literature. First, behavioural analytics is often derived from rich clickstream or transaction-level datasets, whereas many e-commerce firms still rely on aggregated GA4 funnel exports for routine decision-making. Second, cart abandonment theory typically explains why checkout loss occurs, whereas standard funnel reporting mainly shows where users drop off the purchase path. The proposed model was therefore developed to bridge these perspectives by representing checkout disruption as an ordered vector of stages derived from aggregated data. What is new here is the combination of three elements: checkout loss is formalised as an ordered friction-topology vector instead of a set of descriptive drop-off rates; the model is built entirely from aggregated GA4 funnel exports, with no user-level tracking; and the evidence shows that the diagnostic value of device and acquisition context depends on the funnel stage rather than acting uniformly.

The checkout funnel was treated as a sequence of distinct tasks. The transition from Page View to Add to Cart was interpreted as an entry and relevance filter. The transition from Add to Cart to Shipping Info marked the start of the active checkout process. The transition from Shipping Info to Payment Info was associated with delivery assessment, identity disclosure and form completion. In contrast, the transition from Payment Info to Purchase represented the final stage of trust and confirmation. Consequently, friction was expected to be stage dependent rather than uniformly distributed across the funnel. Fig. 1 illustrates the conceptual framework of the checkout funnel and the corresponding friction points.



Figure 1. Conceptual framework of the checkout funnel and friction points

In supplement e-commerce, the first transition has a specific diagnostic meaning: users must evaluate product relevance, credibility, dosage, price and delivery expectations before expressing purchase intent, so the Page View to Add to Cart transition was treated as an entry-stage filter for relevance and reassurance rather than a purely technical checkout step. Post-cart transitions were expected to reflect a different type of friction, more directly related to form completion, delivery assessment, payment confidence and final confirmation.

H1. In supplement e-commerce, the dominant friction point is expected at the Page View-to-Add-to-Cart transition, before explicit cart intent is expressed.

H2. Device-based friction topology is expected to show greater differentiation after cart entry than at the Page View-to-Add to Cart transition.

H3. The medium-friction topology is expected to be stage-dependent, with greater differentiation at the entry and late checkout transitions than at the Add to Cart to Shipping Info transition.

3 Methodology

3.1 Data and measurement context

Two GA4 Funnel exports from an e-commerce property owned by an established supplement brand were analysed. The observation period covered January 3, 2026, to April 2, 2026. The first export was segmented by device category, while the second export was segmented by the first user medium. Supplement e-commerce is understood here as the online retailing of dietary supplements (vitamins, minerals, sports nutrition, and other over-the-counter wellness products) through a brand-owned web shop. The analysed property reflects a Serbian supplement e-commerce context, most relevant to customers in Serbia and the wider region. Five funnel stages were retained in the analysis: Page View, Add to Cart, Shipping Info, Payment Info, and Purchase. These stages correspond to GA4 e-commerce funnel measurement logic, which uses add-to-cart, shipping, payment and purchase events to assess transaction progress (Google, 2026a). The operational definitions of the five stages are summarised in Table 1.

Table 1. Operational definition of funnel stages

Funnel stage	GA4 event / step	Diagnostic meaning
Page View	page_view	Entry exposure and product/landing-page relevance
Add to Cart	add_to_cart	Explicit cart intent
Shipping Info	add_shipping_info	Delivery, identity, and form-entry threshold
Payment Info	add_payment_info	Payment readiness and trust threshold
Purchase	purchase	Final transaction completion

The analysis was conducted as a single-property diagnostic study. It was not intended to provide a universal benchmark for the supplement e-commerce sector. Exported active-user counts were used to compute transition completion and transition friction across various stages and contexts. Minor segments retained in the source tables were not heavily emphasised when user numbers were too low for reliable interpretation. All case data were anonymised at the reporting level. No personally identifiable information was used, and no individual browsing history was reconstructed. The analysis relied on active-user counts exported from the analytics

interface, so the model should be treated as a decision-support representation rather than as a behavioural trace of identifiable users.

The analysis focused on the transition between adjacent funnel stages as the primary unit of measurement, because a total conversion rate collapses the funnel into a single summary outcome. By measuring transitions, the specific points of loss are retained, and each device or medium context can be represented as a topology vector that captures the distribution of loss across the funnel.

3.2 Friction topology formulas

Let $n_{i,c}$ be the number of active users observed at stage i for context c . The transition completion rate $r_i(c)$ was calculated as the ratio between the following and the current stage.

$$r_i(c) = \frac{n_{i+1,c}}{n_{i,c}}, \quad n_{i,c} > 0 \quad (1)$$

Transition friction was defined as the complement of the completion rate, calculated as one minus the proportion of users who progressed to the next stage.

$$F_i(c) = 1 - r_i(c) \quad (2)$$

Friction topology for each context was represented as a vector of ordered stage-level friction values.

$$T(c) = \langle F_1(c), F_2(c), F_3(c), F_4(c) \rangle \quad (3)$$

Context differences were represented as transition-specific contrasts between two topology vectors.

$$\Delta_i(a, b) = F_i(a) - F_i(b) \quad (4)$$

The transitions consisted of Page View to Add to Cart, Add to Cart to Shipping Info, Shipping Info to Payment Info, and Payment Info to Purchase. Formulas (1) and (2) follow the standard definitions of step-completion and drop-off rates used in funnel reporting (Google, 2026b). Formulas (3) and (4) were introduced by the authors: the topology vector extends the drop-off rate into an ordered, comparable representation of the whole funnel, and the contrast in (4) operationalises context differences at the level of individual transitions.

3.3 Hypothesis testing and diagnostic criteria

Each hypothesis was evaluated against the structure of the topology vectors and supported by transition-level statistics. H1 was considered supported if the Page View to Add to Cart transition showed the highest friction value in the overall topology vector. H2 was considered supported if device-based contrasts

(formula 4) and the associated chi-square diagnostics were larger at post-cart transitions than at the entry transition. H3 was considered supported if medium-based differentiation appeared at the entry and late checkout transitions but not at the Add to Cart to Shipping Info transition. For each transition, a chi-square test of independence was performed on the counts of users who did and did not progress, with Cramer's V reported as the effect size and a significance level of $\alpha = .05$.

The diagnostic statistics were interpreted with caution. Large sample sizes can produce statistically significant differences even when the practical effect is minimal, while small segments may yield unstable rates. Cramer's V values of approximately .10, .30, and .50 were used as rough guides for weak, moderate, and strong associations, in line with recent recommendations to avoid rigid universal benchmarks. Automated statistics and dashboards can likewise overstate the importance of small differences when sample sizes are large, and understate meaningful patterns when segments are small (Gandhi et al., 2024). Accordingly, chi-square tests and Cramer's V served as supplementary indicators rather than causal evidence, while the main interpretation relied on the overall pattern of the friction topology.

4 Results

4.1 Overall checkout topology

For brevity, the following stage abbreviations are used in Tables 2 to 5: Page View (PV), Add to Cart (ATC), Shipping Info (SI), Payment Info (PI) and Purchase (PUR). The total funnel consisted of 154,639 active users at Page View, 3,395 at Add to Cart, 1,045 at Shipping Info, 452 at Payment Info, and 317 at Purchase. The largest levels of friction occurred before cart entry, as shown in Table 2. Friction was 97.8% from Page View to Add to Cart, compared with 69.2% from Add to Cart to Shipping Info, 56.7% from Shipping Info to Payment Info, and 29.9% from Payment Info to Purchase.

H1 was supported. The main friction peak appeared at the Page View to Add to Cart transition, before users expressed cart intent. This is significant because in supplement e-commerce, this transition filters relevance and trust factors like credibility, dosage, price, delivery, and brand before adding to the cart. Thus, the largest friction peak isn't a checkout issue, as it happens before users start the checkout process.

Table 2. Overall checkout topology

Transition	Start	Next	Completion	Friction
PV-ATC	154,639	3,395	2.2%	97.8%
ATC-SI	3,395	1,045	30.8%	69.2%
SI-PI	1,045	452	43.3%	56.7%
PI-PUR	452	317	70.1%	29.9%

4.2 Device-based topology

The device topology indicated that mobile and desktop friction at the first transition was almost identical (Table 3, Fig. 2). The mobile friction from Page View to Add to Cart was 97.8%, and the desktop friction was 97.7%. The topology changed after the cart entry. On desktop, friction was markedly higher from Add to Cart to Shipping Info, but much lower from Shipping Info to Payment Info and from Payment Info to Purchase. At the final transition, desktop friction was 10.5%, while mobile friction was 32.7%.

H2 was supported. Device category explained little of the entry stage peak; however, it became diagnostically meaningful after cart entry. The notable disparity in end-stage friction suggests that the final checkout transition should be inspected more carefully for mobile users. This pattern is best treated as a diagnostic signal, not as evidence of a specific causal mechanism. Future user experience (UX) testing would be needed to determine whether the observed difference is related to interface design, payment-gateway behaviour, perceived security, screen size, or other unobserved factors. Tablet observations were excluded because only three users reached the Shipping Info stage, and none progressed further; therefore, the resulting 100.0% SI-PI friction was treated as a small-segment artefact.

Table 3. Device-based friction topology

Device	PV-ATC	ATC-SI	SI-PI	PI-PUR
Total	97.8%	69.2%	56.7%	29.9%
Mobile	97.8%	68.6%	58.3%	32.7%
Desktop	97.7%	73.6%	39.4%	10.5%

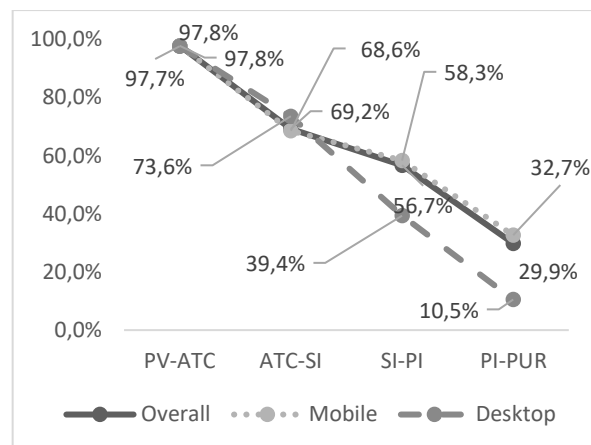


Figure 2. Device-based friction topology vectors

4.3 Medium-based topology

The medium-based topology was more heterogeneous (Table 4). Direct and email traffic had lower entry friction than most other media, while organic and cost-per-click (CPC) traffic had higher Page View-to-Add-to-Cart friction. However, at the final stage, CPC exhibited comparatively low Payment Info-to-

Purchase friction, while paid-social and social showed higher late-stage loss. The acquisition context affects both the readiness to add items to the cart and the willingness to complete later checkout tasks.

H3 was supported with a qualification. Medium-based differences were detected at the Page View to Add to Cart transition and at the late checkout transitions, especially Shipping Info to Payment Info and Payment Info to Purchase. However, the Add to Cart to Shipping Info transition was not clearly differentiated by the first user medium. Acquisition context does not influence all checkout transitions equally. The transition to shipping may represent a high-demand checkout threshold, where delivery disclosure, data-entry effort, and commitment to proceed create friction across media, regardless of the initial acquisition source.

The first user medium is better treated as a stage-sensitive context signal than as a fixed effect of the traffic source. Differences at the entry stage may reflect variation in relevance, audience qualification, or readiness to add items to the cart. In contrast, late-stage differences may indicate varying levels of reassurance required for delivery, payment, or final commitment. These interpretations are diagnostic rather than causal, because the GA4 exports do not include variables such as ad creative, product details, basket value, or user motivation.

Table 4. Selected medium-based friction topology

Medium	PV-ATC	ATC-SI	SI-PI	PI-PUR
paid-social	97.8%	68.2%	68.1%	46.0%
organic	98.9%	69.8%	51.5%	22.2%
cpc	98.3%	65.3%	57.4%	14.3%
direct	95.1%	72.9%	44.9%	24.0%
referral	96.2%	69.4%	57.6%	35.7%
email	94.4%	72.5%	25.0%	23.8%
social	92.1%	65.8%	44.0%	50.0%

4.4 Transition-level diagnostics

Transition diagnostics were performed to determine whether these visual topology differences were also visible in the transition tables (Table 5). Device differences were not highlighted at Page View to Add to Cart, but were present at Shipping Info to Payment Info and Payment Info to Purchase. For the selected media, differences were detected in Page View to Add to Cart and in late checkout transitions. Context effects were stage-specific rather than homogeneous across the funnel. Most Cramer's V values were weak, even when the corresponding chi-square tests were statistically significant.

The diagnostics in Table 5 can be read against the hypotheses. The absence of a significant device difference at PV-ATC ($p = .232$, $V = .003$) confirms that the entry-stage peak is not a device phenomenon, in line with H2. Device associations at SI-PI ($V = .106$) and PI-PUR ($V = .153$) are statistically significant but weak: device category shifts post-cart completion rates in a consistent direction without dominating them.

Medium-based associations are strongest at the late transitions ($V = .220$ and $.261$, approaching moderate strength) and absent at ATC-SI ($p = .089$), which matches the stage-dependent pattern proposed in H3. Taken together, context effects are real but modest, and they concentrate after cart entry rather than spreading uniformly across the funnel.

Table 5. Transition diagnostics used as supporting evidence. n.s. = not significant.

Context	Step	p	Cramer V	Note
Mobile-desktop	PV-ATC	.232	.003	n.s.
Mobile-desktop	SI-PI	<.001	.106	weak
Mobile-desktop	PI-PUR	.001	.153	weak
Selected media	PV-ATC	<.001	.080	very weak
Selected media	ATC-SI	.089	.054	n.s.
Selected media	SI-PI	<.001	.220	weak / moderate
Selected media	PI-PUR	<.001	.261	weak / moderate

5 Discussion

5.1 Conceptual and methodological contribution

All three hypotheses were supported, with one qualified. H1 was supported because the Page View to Add to Cart transition showed by far the highest friction (97.8%), reflecting an entry-stage relevance and reassurance filter. H2 was supported because device differences were absent at entry but significant and directionally consistent after cart entry, where interaction cost becomes task-relevant. H3 was supported with a qualification: medium-based differentiation appeared at the entry and late transitions but not at Add to Cart to Shipping Info, suggesting that the shipping threshold imposes a uniform demand across acquisition contexts. The paper's main scientific contribution is modelling supplement checkout loss as a friction topology. The point is not simply that friction is unevenly distributed across stages; it is that loss can be represented as an ordered pattern in which early and post-cart friction carry different diagnostic meanings. The topology preserves three properties that are usually weakened in descriptive funnel reporting — the location, sequence, and context of loss — so a segment is represented not by a single conversion outcome but by a vector showing how loss is distributed across the purchase path.

There is also a methodological contribution. The model can be derived from aggregated GA4 Funnel exploration exports, so it suits settings without user-level tracking, BigQuery exports or experimental arrangements — particularly small and medium-sized firms that rely on standard GA4 interfaces but still need to locate stage-specific checkout disruption.

Empirically, the case clarifies where the model is most informative. The largest loss occurred before cart entry, while the most context-sensitive differences

appeared after it. This matters because supplement purchases involve product credibility, dosage reassurance, price sensitivity, delivery reliability and payment confidence at different points. Early loss may therefore signal a relevance or reassurance filter, whereas late loss may reflect interaction cost, delivery assessment, perceived risk, payment hesitation or difficulty with final confirmation (Mittal, 2025; Roy & Shaikh, 2024). A single conversion rate would not preserve this distinction. Several earlier studies point in the same direction. The concentration of loss before explicit commitment is consistent with Kukar-Kinney et al. (2022), who found that hesitation and deliberation drive abandonment before checkout tasks begin, and with Mittal (2025), who positions early-journey evaluation as a distinct psychological phase. The higher mobile friction after cart entry mirrors Almeida Lucas et al. (2023), who reported lower task ease on mobile platforms during form-intensive steps. The stage-dependent role of acquisition context refines the journey-level perspective of Koronaki et al. (2023) and Padilla et al. (2025): its diagnostic value varies by funnel position rather than acting as a stable segment effect. The contribution relative to these studies is methodological as much as empirical, because the same stage-sensitive reading is obtained here from aggregated export data rather than from clickstream or survey data.

The medium-based results refine the role of acquisition context: the first user medium did not act as a constant segment effect, and its diagnostic value changed by stage. Entry-stage differences suggest that acquisition context shapes initial relevance and readiness to enter the cart, while late-stage differences point to payment confidence, delivery evaluation and final commitment and do not behave uniformly across media. The weak differentiation at the Add to Cart to Shipping Info transition suggests that some checkout thresholds may be overly demanding across contexts.

5.2 Managerial use and practical implications

For supplement e-commerce merchants, friction topology can be used in recurring analytics reports to track where checkout losses concentrate over time. A weekly or monthly comparison of topology vectors can show whether friction is increasing at the entry, shipping, payment, or final confirmation stage. For UX teams, this helps prioritise what to inspect first: mobile usability, form complexity, delivery clarity, checkout transparency, or payment-stage confidence (Ho et al., 2022; Saha et al., 2023). In terms of the customer journey, the model does not redesign the journey itself; it shows where it breaks down. By identifying the stage at which most users are lost, merchants can direct interventions at the actual point of disruption rather than reworking the entire funnel, and each diagnostic cycle shortens the path from observed loss to targeted improvement.

The medium topology can separate traffic quality from checkout experience for marketing teams (Koronaki et al., 2023). When entry friction is high within a medium, managers should first examine landing-page relevance, campaign-message congruence and audience qualification; when friction is concentrated in the final stages, they should focus on payment reassurance, price transparency, shipping disclosure and trust cues (Mittal, 2025; Roy & Shaikh, 2024). The model can thus serve as a low-cost prioritisation tool before more expensive testing begins.

To make the model's diagnostic value more actionable, Table 6 translates the observed friction-topology patterns into practical recommendations for supplement e-commerce merchants.

Table 6. Practical recommendations for supplement e-commerce merchants

Observed friction pattern	Diagnostic interpretation	Recommended merchant action
High Page View to Add to Cart friction	Users are not sufficiently convinced before expressing cart intent	Improve product-page relevance, dosage clarity, benefit communication, reviews, trust badges and delivery visibility before cart entry
Similar entry friction across devices	Device category does not explain the main pre-cart loss	Focus first on product relevance, offer clarity and reassurance rather than device-specific redesign at the entry stage
Higher mobile friction after cart entry	Mobile users may face greater interaction cost, payment hesitation or confirmation difficulty	Audit mobile checkout forms, button visibility, loading speed, payment gateway behaviour and final confirmation screens
High Add to Cart to Shipping Info friction	Users hesitate when checkout requires identity, delivery or commitment information	Reduce form burden, show delivery options earlier, clarify shipping costs and allow guest checkout where possible
High Shipping Info to Payment Info friction	Delivery conditions or form completion may create resistance	Improve delivery transparency, validate forms in real time, reduce unnecessary fields and show estimated delivery time clearly
High Payment Info to Purchase friction	Final-stage trust, payment confidence or unexpected cost issues may block completion	Strengthen payment reassurance, display total cost before payment, highlight secure payment methods and check for payment-gateway errors
Medium-specific entry friction	Some traffic sources may bring less qualified or less aligned users	Review campaign-message congruence, landing-page fit, audience targeting and product-offer alignment
Medium-specific late-stage friction	Users from some channels may need more reassurance before final purchase	Adapt checkout reassurance, retargeting messages and trust cues by acquisition context

These recommendations should not be interpreted as causal evidence of specific checkout problems, but

rather as a prioritisation framework for deciding which checkout stages to audit first.

5.3 Limitations

Several limitations should be acknowledged. First, the analysis relied on a single GA4 property, one established supplement brand and one observation window, so the findings are case-based rather than a sector-wide benchmark. Second, only aggregated counts were available; user-level paths, repeated visits, timing between steps, product categories, basket values, coupon usage, stock availability, shipping costs, payment errors and form-error events were not included. Third, the first user medium and device category followed GA4 breakdown logic, so users who changed devices or channels mid-journey could not be re-attributed in the exported tables. Fourth, the model did not explicitly incorporate psychological constructs.

Cognitive load, perceived ease of use, perceived risk, and trust were employed solely as theoretical interpretative frameworks, not as measured variables. Fifth, no causal inference was attempted; the observed differences identify where friction concentrates, not why it occurs. Future research should integrate friction topology with GA4 BigQuery exports, session-level timestamps, product-level variables, form-error logging, and controlled checkout experiments. In practice, the model should also be used alongside event audits, tag validation, and regular comparisons with order-management records. At the same time, these limitations concern the empirical case rather than the method itself. The model itself is not tied to this property: formulas (1) to (4) require only stage-level user counts so that the same diagnostic can be applied to any e-commerce funnel with ordered stages, including other product categories, other markets, differently defined funnels, and analytics platforms other than GA4. Multi-brand and multi-sector replication would establish whether the entry-stage friction peak and the post-cart context sensitivity observed here are sector-typical or property-specific.

6 Conclusion

This paper develops a friction-topology model for GA4 checkout export data from a well-known supplement e-commerce brand. Instead of a single conversion rate, aggregated counts were used to construct transition-loss vectors, allowing precise localisation of drop-offs by stage, device, and acquisition channel. Across the three hypotheses, H1 and H2 were supported, while H3 was supported with a qualification regarding the Add to Cart-to-Shipping Info transition.

The largest friction peak occurs before cart entry, while differences across devices and media become clearly visible only after users add products to the cart. The model can be implemented directly from standard GA4 Funnel exploration exports, without user-level

tracking or BigQuery access, making it practical for analysts, UX, and marketing teams working with routine GA4 data.

Further work should test the model across multiple brands, longer observation periods, and more granular event-level data. Future validation should add event-level variables such as basket value, promotion type, payment method and form errors.

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