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Delivery Uncertainty, Perceived Risk, and Cash-on-Delivery Refusal in Bangladesh

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Abstract

This study examines whether last-mile delivery uncertainty increases customers' intention to refuse a cash-on-delivery (COD) parcel at the doorstep, and whether perceived delivery risk mediates this relationship in Bangladesh's e-commerce sector. *Design:* Survey data were collected from 176 Bangladeshi online shoppers with recent COD experience and analysed using PLS-SEM in SmartPLS 4. The analysis included discriminant-validity testing, bootstrapped hypothesis testing, mediation analysis, and out-of-sample predictive assessment. Delivery uncertainty significantly increased perceived delivery risk ($\beta = .393$, $p < .001$), which significantly increased COD doorstep refusal intention ($\beta = .458$, $p < .001$). The direct effect of delivery uncertainty on refusal intention was not significant ($\beta = .055$, $p = .489$), whereas the indirect effect through perceived delivery risk was significant ($\beta = .180$, $p < .001$), indicating indirect-only mediation. DU and PDR also showed strong discriminant validity (HTMT = .415). Managers should address customers' risk perceptions through accurate order confirmation, timely reassurance, and clear service-recovery guarantees rather than relying on tracking visibility alone. The study distinguishes delivery uncertainty from perceived delivery risk at the delivery stage and links this psychological mechanism to COD doorstep refusal and the resulting reverse-logistics burden in an emerging market.

Keywords: Cash on delivery, Delivery uncertainty, Last-mile logistics, Perceived risk, PLS-SEM, Reverse logistics

Paper type. Research paper

1. Introduction

Cash-on-delivery (COD) remains the default payment method in Bangladesh's e-commerce sector, with recent industry estimates placing COD preference above 90 per cent of online transactions (International Trade Administration, 2026). The importance of payment arrangements is also visible in Bangladeshi online-shopping research, where payment mode appears among the factors shaping consumers' online purchasing decisions (Azad, Hasan, & Islam, 2022). Unlike prepaid e-commerce, a COD transaction is not economically complete until the customer physically accepts the parcel at the doorstep; the courier, not a payment gateway, is the final checkpoint of the sale. That makes the last mile more than a logistics problem. It is the point at which a customer can still decide whether the transaction goes through.

The last mile in emerging e-commerce markets isn't always a smooth ride. Customers may have questions about what will happen next if the seller is unable to dispatch the ordered items, inaccurate shipping information, the items are out of stock, or there is weak coordination between the seller and third-party couriers (Lim et al., 2018; Dhir, 2026). The same can be found in the evidence from Bangladesh as well: low trust and deficiencies in supply-chain management are shown to be important consumers' concerns about the purchase of electronic products online (Khan et al., 2022). Studies on real-time data collection and end-to-end tracking also illustrate the vulnerability of logistics and demand decisions due to information

gaps (Hasan & Khan, 2022). Less well understood is what happens in the event that this operational uncertainty extends all the way to the customer, where the forward supply chain should stop.

In a COD setting, that uncertainty is what makes the customer have a tangible choice that prepaid commerce doesn't have: refuse the parcel. The situation is therefore intriguing and fascinating from the perspective of consumer behaviour and supply chain performance. Very much before a purchase is made, a large amount of research has been conducted on perceived risk in online purchasing (for example, a systematic review in 2024 combined 133 studies on perceived risk and purchase intention (Phamthi, 2024)). Meanwhile, research on the supply chain has focused on delivery uncertainty as an operational issue that has to do with information, coordination, and execution. Much less has been written about the mechanism that links the two streams at the doorstep. Research at Work in Supply Chain Insider also highlights the fact that the supply chain does not end when the product is delivered but when the customer receives it, and that communication to the customer is an integral part of the functioning of the supply chain (Islam, Ruksana, Raihan, Zahin, & Afrin, 2022). The unanswered question is therefore quite practical: when a delivery feels uncertain after the order has already been placed, does the customer interpret that uncertainty as risk, and does that risk make refusal more likely?

This study addresses that question directly. We ask whether last-mile delivery uncertainty increases customers' intention to refuse a COD parcel at the doorstep, and whether perceived delivery risk - customers' evaluative appraisal of the potential loss, inconvenience, or dissatisfaction that could follow from accepting an uncertain delivery - explains this relationship. Grounded in Perceived Risk Theory (Bauer, 1960) and Protection Motivation Theory (Rogers, 1975), we position doorstep refusal as a protective, loss-avoidant consumer response to risk accumulated during the delivery process itself, rather than at the point of purchase.

The study offers two contributions. Theoretically, it treats delivery uncertainty and perceived delivery risk as conceptually and empirically distinct constructs operating sequentially at the delivery stage - a distinction prior work has debated rather than settled (Mitchell, 1999; Quintal et al., 2010) - and extends this reasoning to a behavioural outcome, COD doorstep refusal, not previously modelled as a mediated consequence of delivery-stage risk perception. Practically, it reframes COD refusal for supply chain managers: not simply a customer-service or courier-performance metric, but a predictable, psychologically grounded response to uncertainty that, left unaddressed, manufactures avoidable reverse logistics cost.

The remainder of the paper proceeds as follows. Section 2 reviews the relevant literature and develops four hypotheses. Section 3 presents the conceptual framework. Section 4 details the methodology. Sections 5 and 6 report and discuss these findings.

2. Literature Review and Hypothesis Development

2.1 Last-mile delivery uncertainty in e-commerce supply chains

Delivery uncertainty is easiest to see in the gap between what a customer expects and what the logistics system actually does. An order may have been accepted, dispatched, and recorded a tracking number, but the customer is still uncertain about the time it takes to delivery or if the supposed delivery time frame matters in the least. This uncertainty can come about due to issues like unexpected delays, routing or handling issues, poor tracking data, or poor coordination between sellers, warehouses, and third-party couriers. The problem is made more apparent with the advent of e-commerce as the physical travel and the flow of information are divided between a number of actors, and the customer has little direct control over either of them (Lim et al., 2018). In the same vein, weaknesses within the supply chain can impact customers' trust and willingness to make an online purchase directly, as revealed by research published in Supply Chain Insider (Khan et al., 2022).

Technology is supposed to fill this gap, but it doesn't do the trick all of the time. The idea of estimated delivery windows, tracking numbers, and status updates is to eliminate ambiguity; if they don't match what the customer is seeing, then the ambiguity becomes more apparent. Timeliness – defined as delivering when promised – has long been recognized in the logistics service quality literature as one of the basic service quality dimensions (Mentzer et al., 1999; Mentzer et al., 2001). It is the idea we use here, but the emphasis is on the customer's perception of predictability. This emphasis is also consistent with Bangladeshi work arguing for real-time data and end-to-end tracking to improve logistics operations (Hasan & Khan, 2022).

This is a topical concern in the context of Bangladesh. Strong dependency on cash-on-delivery (Dhir, 2026) and a fragmented courier network and uneven infrastructure outside major cities are cited as challenges in last-mile delivery, which is a major weakness in the country's e-commerce sector. Other related challenges in the supply chain within Bangladesh's e-commerce and distribution system are also identified from other Supply Chain Insider studies, such as delivery, coordination, traceability, and information flow issues (Haque et al., 2022; Hasan & Khan, 2022). However, these conversations are more about the operational aspects of the problem. Much less is said about the customer's mental reaction when these operational shortcomings become apparent during a real delivery.

This is the gap the present study addresses. Existing research has extensively examined delivery uncertainty as an operational, firm-level phenomenon, and separately examined perceived risk as a driver of pre-purchase intention (Phamthi, 2024). Comparatively little research has examined delivery uncertainty as a customer-facing psychological experience unfolding after the purchase has been made, at the specific moment - doorstep delivery under COD - where that experience

can translate directly into a reverse flow of goods. We position delivery uncertainty (DU) as the independent variable in this study: the customer's perceived unpredictability regarding whether and when a COD order will actually be delivered.

2.2 Perceived risk theory and the uncertainty-risk distinction

The concept of perceived risk theory is based on a simple premise: a purchase is never a sure thing because the outcomes of such a purchase cannot be predicted, and some outcomes of a purchase may be undesirable (Bauer, 1960). Subsequent studies divided this general concept into specific types of risk. For instance, Cox (1967) separated the financial, temporal, and effort risks into different categories,s and Cunningham (1967) suggested categories such as performance risk, financial risk, opportunity risk, and safety risk. Jacoby and Kaplan (1972) organised perceived risk into five widely used categories - financial, functional, physical, psychological, and social - and Stone and Grønhaug (1993) further highlighted time and convenience as important dimensions. Those latter dimensions fit the delivery context especially well because waiting, arranging receipt, and dealing with repeated delivery attempts all consume customer time.

However, there is a more basic question for this study: "Is uncertainty the same as perceived risk? There is no one correct answer. Risk and uncertainty can be separated empirically from the work of others, and Mitchell (1999) considers uncertainty to be a part of risk. Quintal et al. (2010), for example, showed that perceived risk and perceived uncertainty were distinct factors and that they had different downstream consequences. But this matter is important because the first information problem a customer faces here may be one where he or she doesn't know what will happen to the delivery, and then an evaluative judgement of what that uncertainty may mean to the customer. Moreover, findings from Bangladeshi online shopping indicate that payment conditions along with trust impact the informational and evaluative stage of online transactions, further supporting the need to maintain these stages conceptually distinct (Azad et al., 2022; Khan et al., 2022).

In line with this reasoning, the present study regards delivery uncertainty and perceived delivery risk as two distinct concepts. These are separated at the item level: delivery uncertainty refers to the customer's informational perception of delivery uncertainty, and perceived delivery risk refers to the judgment that accepting the delivery will result in financial loss, functional disappointment, psychological discomfort, or wasted time. This separation is thus a theoretically driven one and not merely a measurement decision. Uncertainty creates a situation in which an appraisal is needed; perceived risk is the appraisal itself. We define perceived delivery risk (PDR), the mediating variable in this study, as the extent to which delivery uncertainty leads the customer to believe that accepting the delivery carries a meaningful chance of financial loss, functional disappointment, psychological discomfort, or wasted time.

2.3 From risk perception to protective behaviour: COD doorstep refusal

Perceived risk does not remain a purely cognitive state; consumer behaviour research has long linked heightened risk perception to avoidance and protective responses. Protection Motivation Theory (Rogers, 1975; Maddux and Rogers, 1983), developed originally to explain responses to health threats, proposes that once a threat is appraised as sufficiently severe and personally relevant, individuals engage in a coping appraisal that can result in a protective, threat-avoidant behavioural response. Although developed outside a commercial context, this logic transfers naturally to the delivery setting: a customer who appraises an uncertain COD delivery as risky is positioned to engage in a protective response of their own — and under COD, that response is available in a form prepaid commerce does not offer: outright refusal of the parcel at the doorstep, before payment is made and before the transaction is finalised.

Reverse logistics — the backward flow of goods from customer to seller — has long been recognised as a costly, often under-planned component of supply chain management (Tibben-Lembke, 2002). A doorstep refusal is a direct, avoidable trigger of this backward flow, and one that occurs at the point of maximum sunk last-mile cost. This study therefore deliberately distinguishes doorstep refusal from pre-dispatch order cancellation, a behaviourally and economically different event: cancellation typically occurs before a courier is dispatched and incurs comparatively little logistics cost, whereas doorstep refusal occurs after the full last-mile journey has already been completed. It is this later-stage refusal that generates the reverse logistics cycle motivating this study's supply chain framing. Because no existing validated scale measures this specific behaviour, items were developed for this study following the standard behavioural-intention phrasing convention established in the Theory of Planned Behavior (Ajzen, 1991), rather than borrowing item content from an unrelated behavioural domain.

We term this outcome COD doorstep refusal intention (CRI): the customer's self-reported likelihood of declining to accept a COD parcel specifically at the moment the courier arrives.

2.4 Hypothesis development

Delivery uncertainty is, by definition, a state in which the customer cannot verify that a transaction will conclude as expected. Even without an intervening risk appraisal, this unresolved unpredictability plausibly increases the likelihood that a customer, faced with an unfamiliar courier and an unconfirmed parcel at the door, defaults to caution and declines to accept it — particularly given that COD, unlike prepaid delivery, imposes no financial or procedural cost to refusing on the spot. We therefore expect a direct, positive relationship between delivery uncertainty and refusal intention, independent of any mediating appraisal.

H1. Delivery uncertainty has a positive direct effect on COD doorstep refusal intention.

Perceived risk theory holds that uncertainty about a decision's outcome is a necessary precondition for risk perception to form (Bauer, 1960; Mitchell, 1999): when the customer cannot verify that an order will arrive as promised, they cannot verify that the transaction will conclude safely, and it is this unverifiability that risk perception is understood to form around. Applied to the delivery context, greater delivery uncertainty should therefore be associated with a stronger appraisal of potential financial, functional, psychological, and time-related loss.

H2. Delivery uncertainty has a positive effect on perceived delivery risk.

Protection Motivation Theory (Rogers, 1975; Maddux and Rogers, 1983) predicts that once a threat is appraised as sufficiently costly, individuals engage in threat-avoidant behaviour. Refusing a COD parcel is precisely such a behaviour: it is available at zero financial cost to the customer and directly forecloses the specific losses that a risk appraisal identifies as possible. We therefore expect perceived delivery risk to increase refusal intention directly.

H3. Perceived delivery risk has a positive effect on COD doorstep refusal intention.

Taken together, H1 through H3 imply that part of delivery uncertainty's effect on refusal intention operates indirectly, by first shaping the customer's risk appraisal, which then motivates the protective response of refusal. This is consistent with the broader logic of Protection Motivation Theory, in which a threat's behavioural consequences are understood to be mediated by its cognitive appraisal (Rogers, 1975). We therefore expect perceived delivery risk to at least partially mediate the relationship between delivery uncertainty and refusal intention.

H4. Perceived delivery risk mediates the relationship between delivery uncertainty and COD doorstep refusal intention.

3. Conceptual Framework

Figure 1 summarises the conceptual model tested in this study. Delivery uncertainty (DU) is positioned as the independent variable, perceived delivery risk (PDR) as the mediating variable, and COD doorstep refusal intention (CRI) as the dependent variable. The model specifies a direct path from DU to CRI (H1), a path from DU to PDR (H2), and a path from PDR to CRI (H3); the indirect path formed by H2 and H3 in combination constitutes the mediation hypothesis (H4). This is a partial-, not full-, mediation specification: consistent with the theoretical argument in Section 2.4, delivery uncertainty is expected to influence refusal intention both directly and indirectly through perceived delivery risk, rather than exclusively through one pathway. The model is deliberately parsimonious: rather than crowding a first empirical test of this mechanism with additional constructs, the three-variable structure isolates the specific psychological chain — from an informational state, to an evaluative appraisal, to a protective behavioural intention — that this study argues has not previously been tested at the delivery stage of a cash-on-delivery transaction.

Figure 1. Conceptual Framework

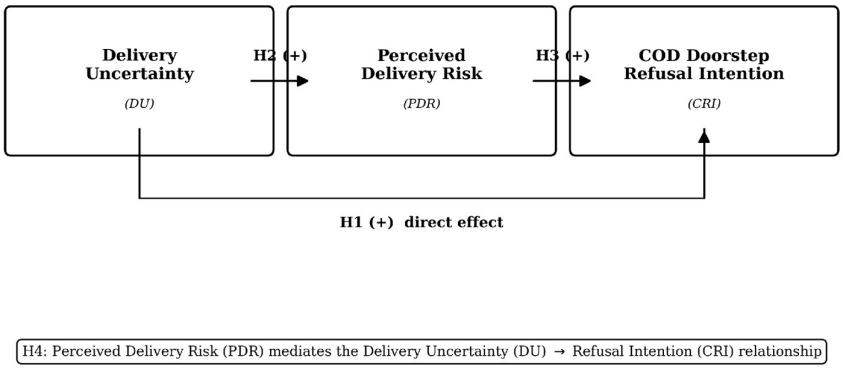


Figure 1. Conceptual framework and hypothesised paths.

4. Methodology

4.1 Research design and context

This study employs a cross-sectional quantitative survey design, appropriate for testing a hypothesised mediation model at a single point in time (Hair et al., 2022). The study context is Bangladesh's business-to-consumer e-commerce sector, selected because of its unusually high reliance on cash-on-delivery — a payment arrangement in which the transaction remains reversible up to the moment of physical handoff, making it, unlike prepaid e-commerce, a setting in which delivery-stage risk perception can translate directly into an observable behavioural intention (refusal) rather than remaining a purely attitudinal outcome.

4.2 Sampling and data collection

The respondents constitute the target population, which includes online shoppers of Bangladeshi age 18 years and above who have placed at least one COD order, especially those who reported delayed, uncertain, and otherwise problematic deliveries,s as they are the most suitable to be able to assess the constructs. The respondents were selected through personal and institutional networks, such as a nationwide network of youth volunteers, social media groups based on online shopping and e-commerce experiences in Bangladesh, and snowball sampling. Quotas were checked by division, age and gender, and outreach efforts were made to under-represented cells to overcome the demographic skews that are associated with convenience sampling, but the sample was still non-probability; this limitation is made explicit in the Discussion.

The survey link was distributed to 250 contacts across these channels; 217 responses were received (86.8% response rate). Following the screening protocol, 23 respondents were excluded for not having placed a COD order and a further 18 for failing the embedded attention-check item, leaving a final analytic sample of 176 respondents (81.1% of received responses) — the sample on which all results, demographic profile, and analyses reported below are based.

Characteristic	Distribution
Age	18–24: 24.4% · 25–34: 24.4% · 35–44: 26.7% · 45+: 24.4%
Gender	Male: 51.7% · Female: 44.9% · Prefer not to say: 3.4%
Occupation	Self-employed/Business: 19.9% · Employed (Private): 17.0% · Other: 17.0% · Employed (Government): 15.9% · Student: 15.3% · Homemaker: 14.8%
Division	Chattogram: 14.8% · Barishal: 14.8% · Rajshahi: 14.2% · Sylhet: 13.6% · Mymensingh: 12.5% · Rangpur: 10.2% · Khulna: 10.2% · Dhaka: 9.7%
Area type	Rural: 35.2% · Semi-urban: 33.5% · Urban: 31.2%
Online shopping frequency (per month)	Less than 1: 29.0% · 1–2: 18.2% · 3–5: 29.0% · More than 5: 23.9%
Typical COD order value (BDT)	Under 500: 21.0% · 500–1,500: 28.4% · 1,500–3,000: 27.8% · Over 3,000: 22.7%
Most-ordered product category	Clothing/Fashion: 18.2% · Books & Stationery: 18.2% · Cosmetics & Beauty: 17.0% · Food & Groceries: 17.0% · Electronics: 15.3% · Other: 14.2%
Trust in sellers/platforms	Very low: 23.9% · Low: 15.9% · Neutral: 21.0% · High: 14.8% · Very high: 24.4%
Recency of most recent COD order	Within last month: 33.0% · 1–3 months: 26.1% · 3–6 months: 22.2% · 6+ months: 18.8%
Past COD refusals/cancellations (6 months)	0: 47.2% · 1: 25.0% · 2: 13.6% · 3: 8.5% · 4 or more: 5.7%

Table 1. Respondent and order profile (n = 176). Divisional and demographic spread is broadly even, consistent with the quota-monitored recruitment approach described above.

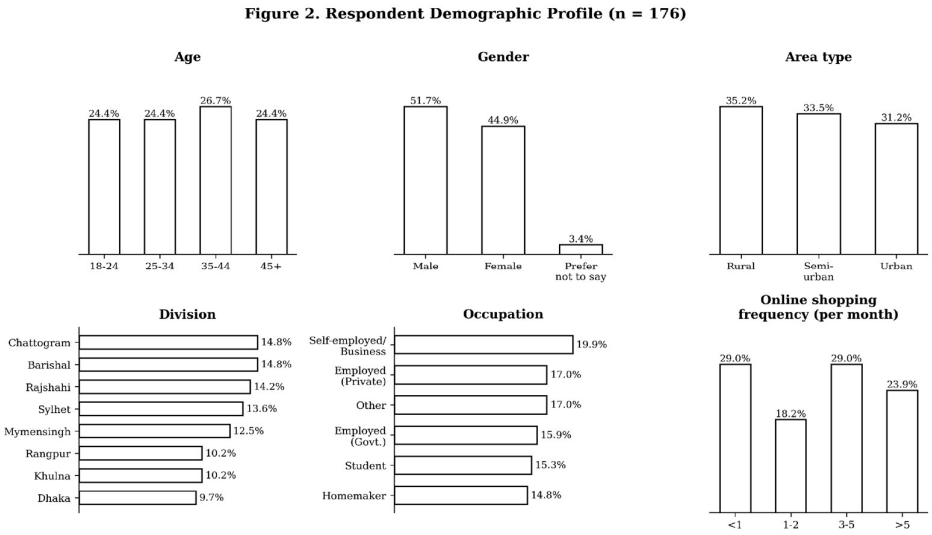


Figure 2. Respondent demographic profile (n = 176).

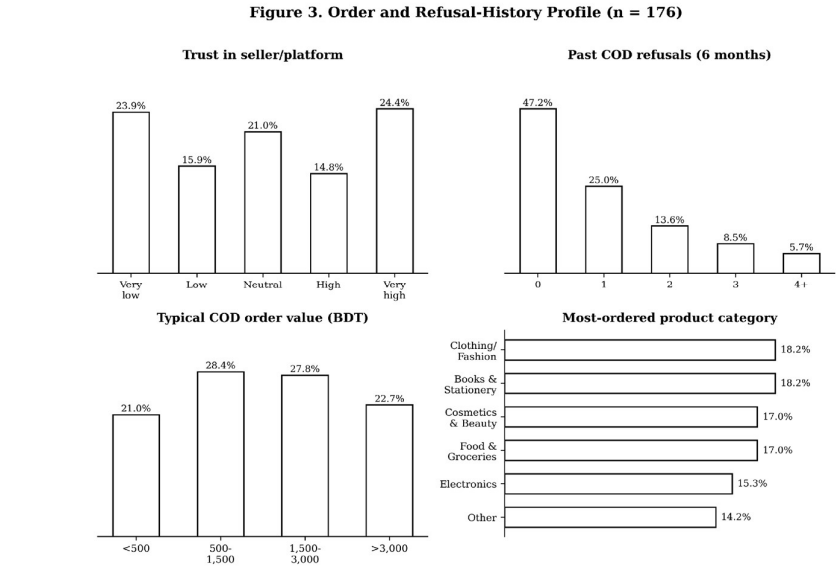


Figure 3. Order value, trust, and refusal-history profile (n = 176).

4.3 Measurement instrument

All constructs were measured using multi-item, five-point Likert scales (1 = strongly disagree to 5 = strongly agree), anchored to respondents' most recent COD delivery experience to reduce recall bias. Delivery uncertainty (five items) was adapted from the timeliness dimension of the Logistics Service Quality scale (Mentzer et al., 1999; Mentzer et al., 2001), reworded from an objective performance framing to a subjective predictability framing consistent with this study's construct definition. Perceived delivery risk (five items) was adapted from Jacoby and Kaplan's (1972) financial, functional, and psychological risk dimensions, together with the time/convenience risk dimension identified by Stone and Grønhaug (1993); the physical and social risk dimensions in Jacoby and Kaplan's original typology were judged not conceptually applicable to this context and were excluded. COD doorstep refusal intention (four items) was custom-developed following the behavioural-intention item-writing convention established by Ajzen (1991), since no validated scale for this specific behaviour exists in the literature. One attention-check item was embedded to support data-quality screening. Full item wording and sourcing are summarised in Table 2. In addition to the three focal constructs, the instrument collected six descriptive/control variables — typical order value, product category, seller/platform trust, division, area type, and recalled refusal frequency — which are not part of the hypothesised structural model but are used in Section 6 to probe alternative explanations and enrich interpretation of the main findings.

Construct	Definition	Item Source	Items	Scale
Delivery Uncertainty (DU) Independent variable	Perceived unpredictability of whether/when a COD order will be delivered.	Mentzer et al. (1999, 2001) — LSQ timeliness dimension, reframed from performance to predictability.	5	5-pt Likert
Perceived Delivery Risk (PDR) Mediator	Evaluative appraisal of potential loss from accepting an uncertain delivery.	Jacoby and Kaplan (1972); Stone and Grønhaug (1993) — financial, functional, psychological, and time/convenience risk.	5	5-pt Likert
COD Doorstep Refusal Intention (CRI) Dependent variable	Self-reported likelihood of refusing a COD parcel at the doorstep.	Custom content (no prior scale exists); item structure follows Ajzen (1991) behavioural-intention convention.	4	5-pt Likert

Table 2. Measurement items, definitions, and sources.

4.4 Common method bias

Because all constructs were measured via self-report from a single respondent at a single point in time, common method bias is a relevant threat to validity (Podsakoff et al., 2003; MacKenzie and Podsakoff, 2012). Procedural remedies were applied during instrument design: constructs were presented in psychologically separated blocks rather than interleaved, response-scale presentation was varied slightly across blocks, and respondent anonymity was assured to reduce social-desirability bias (Podsakoff et al., 2012). Statistically, common method bias was assessed using Harman's single-factor test and the full-collinearity variance inflation factor (VIF) approach recommended specifically for PLS-SEM (Kock, 2015), with inner VIF values below 3.3 taken as evidence that common method bias is not a serious concern.

4.5 Data analysis technique

Partial least squares structural equation modelling (PLS-SEM), implemented in SmartPLS 4 (Ringle et al., 2024), was selected as the analysis technique, for three reasons. First, it accommodates the exploratory, theory-extending nature of a model testing a mediation chain not previously examined in this context (Hair et al., 2022). Second, PLS-SEM requires that discriminant validity between latent constructs — assessed via the Fornell-Larcker criterion (Fornell and Larcker, 1981) and the heterotrait-monotrait ratio (HTMT; Henseler et al., 2015) — be established before structural paths are interpreted; because delivery uncertainty and perceived delivery risk are conceptually adjacent constructs whose separability is itself a claim this study makes explicitly (Section 2.2), this measurement-model gate provides a direct empirical check on that claim rather than an assumption. An HTMT value below 0.85 between delivery uncertainty and perceived delivery risk was treated as the threshold for proceeding to structural model interpretation. Third, hypothesis testing (H1–H3) relied on bootstrapped path coefficients (5,000 resamples, bias-corrected and accelerated confidence intervals), and the mediation hypothesis (H4) was tested via the bootstrapped indirect effect of delivery uncertainty on refusal intention through perceived delivery risk, with the resulting pattern of direct and indirect effects classified according to Zhao et al.'s (2010) typology of mediation rather than the earlier causal-steps approach (Hair et al., 2019).

5. Results

5.1 Respondent profile

The analytic sample (n = 176) is profiled in Table 1 and Figures 2–3. The distribution of respondents across the eight administrative divisions of Bangladesh and urban and rural areas of Bangladesh was also broadly distributed as described in Section 4.2, in a quota-monitored recruitment strategy (9.7%–14.8% each administrative division and 31.2%–35.2% each urban, semi-urban and rural). The sample was not skewed towards any one category of occupation, and just over half of those responding (52.8%) reported rejecting or canceling a COD order in the past six months on their own behalf, suggesting the behaviour being studied is not uncommon among this population, but rather is a common occurrence.

5.2 Measurement model assessment

Indicator reliability, internal consistency, and convergent validity were assessed following Hair et al.'s (2022) guidelines. All outer loadings exceeded the recommended 0.70 threshold, ranging from 0.883 to 0.922 (Table 3). Cronbach's alpha exceeded 0.93 for all three constructs, composite reliability (ρc) exceeded 0.95 for all three, and average variance extracted (AVE) exceeded the 0.50 threshold for all three (DU = .797, PDR = .798, CRI = .834), indicating strong indicator reliability, internal consistency, and convergent validity throughout the measurement model.

Construct	Item	Loading	α	CR (ρa)	CR (ρc)	AVE
DU	DU1	.894				
DU	DU2	.888				
DU	DU3	.883	.936	.942	.951	.797
DU	DU4	.900				
DU	DU5	.898				
PDR	PDR1	.896				
PDR	PDR2	.911				
PDR	PDR3	.891	.937	.939	.952	.798
PDR	PDR4	.884				
PDR	PDR5	.884				
CRI	CRI1	.922				
CRI	CRI2	.909	.934	.948	.953	.834
CRI	CRI3	.922				
CRI	CRI4	.900				

Table 3. Measurement model: outer loadings and construct-level reliability/validity (α, CR, AVE shown once per construct).

The Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) were used to test the discriminant validity. The square root of AVE was higher than the correlation with all the other constructs, which indicates a satisfactory Fornell-Larcker criterion for every construct (Table 4). All of the HTMT values were significantly lower than the conservative limit of 0.85, and especially the gap between delivery uncertainty and perceived delivery risk (HTMT = 0.415), which was central to the measurement concern that was raised in Section 2.2, based on empirical separability. This finding also offers empirical evidence that delivery uncertainty and perceived delivery risk in this context should be considered separate constructs, and not aspects of one.

Fornell–Larcker criterion (diagonal = √AVE)

	CRI	DU	PDR
CRI	.913		
DU	.235	.893	
PDR	.479	.393	.894

Heterotrait-monotrait ratio (HTMT)

	CRI	DU	PDR
CRI			
DU	.246		
PDR	.501	.415	

Table 4. Discriminant validity: Fornell-Larcker criterion and HTMT.

Collinearity was not a concern at either the indicator level (outer VIF 3.11–3.79, all below the conservative threshold of 5) or the structural level (inner VIF 1.00–1.18, all well below 3.3).

5.3 Common method bias

Because all constructs were measured via self-report at a single point in time, common method bias (CMB) was assessed using two convergent tests. Harman's single-factor test showed the first unrotated factor explained 46.9% of total variance, below the 50% threshold conventionally taken to indicate a serious CMB threat. The full-collinearity VIF test (Kock, 2015) showed all inner VIF values at or below 1.18, far below the 3.3 threshold. Both tests converge on the conclusion that common method bias is unlikely to materially threaten the results.

5.4 Structural model and hypothesis testing

The structural model explained 15.5% of variance in perceived delivery risk (R^2 = .155, adjusted R^2 = .150) and 23.2% of variance in COD doorstep refusal intention (R^2 = .232, adjusted R^2 = .223) — modest effect sizes by Chin's (1998) guidelines, and expected for a deliberately parsimonious first test of a novel psychological chain (see Section 9). Figure 4 reproduces the estimated SmartPLS model, showing indicator loadings, path coefficients, and R^2 values together.

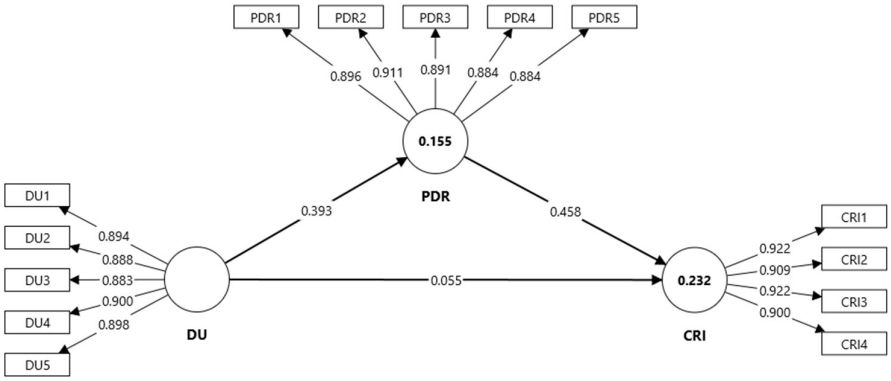


Figure 4. Estimated structural model (SmartPLS output): indicator loadings, path coefficients, and R^2.

Hypotheses were tested via bootstrapping (5,000 resamples, bias-corrected and accelerated 95% confidence intervals). Results are summarised in Table 5. Delivery uncertainty had a significant, substantial positive effect on perceived delivery risk (β = .393, t = 6.267, p < .001, f^2 = .183), supporting H2. Perceived delivery risk had a significant, substantial positive effect on COD doorstep refusal intention (β = .458, t = 6.912, p < .001, f^2 = .231), supporting H3. The direct effect of delivery uncertainty on refusal intention, however, was small and not statistically significant (β = .055, t = 0.692, p = .489, f^2 = .003; 95% CI [-.095, .212], spanning zero); H1 was therefore not supported.

H	Path	β	t	p	95% CI	f^2	Decision
H1	DU → CRI (direct)	.055	0.692	.489	[-.095, .212]	.003	Not supported
H2	DU → PDR	.393	6.267	<.001	[.266, .510]	.183	Supported
H3	PDR → CRI	.458	6.912	<.001	[.316, .578]	.231	Supported

Table 5. Structural path estimates and hypothesis testing (bootstrapped, 5,000 resamples).

A post-hoc power analysis clarifies this null result. Achieved power to detect the DU→CRI path at α = .05 was low (18.1%), and detecting an effect of this size (f^2 = .003) with 80% power would require a sample in excess of 2,000 — more than eleven times the present sample. By contrast, achieved power for the DU→PDR and PDR→CRI paths exceeded 99.9%, both comfortably powered at n = 176. The non-significant direct effect is therefore better read as evidence of a genuinely negligible direct pathway than as a Type II error born of insufficient power — a distinction developed further in Section 6.

5.5 Mediation analysis

H4 proposed that perceived delivery risk mediates the relationship between delivery uncertainty and refusal intention. The specific indirect effect (DU→PDR→CRI) was positive and significant (β = .180, t = 4.709, p < .001, 95% CI [.111, .261], excluding zero), supporting H4. The total effect of delivery uncertainty on refusal intention was also significant (β = .235, t = 3.180, p = .001). Given that the direct effect (H1) was not significant while the indirect effect was, this

pattern classifies as indirect-only mediation in Zhao et al.'s (2010) typology — the pattern earlier termed 'full mediation' under the Baron and Kenny (1986) causal-steps approach. Substantively, delivery uncertainty's entire estimated effect on doorstep refusal intention operates through perceived delivery risk; no evidence was found of a risk-independent pathway from uncertainty to refusal. A structurally similar indirect-only pattern has been reported elsewhere in online retail: Oghazi et al. (2018) found that return-policy leniency affects online purchase decisions entirely through consumer trust rather than directly, lending broader plausibility to appraisal-based mechanisms fully carrying the effect of a structural antecedent on a downstream e-commerce decision.

Path	β	t	p	95% CI	Result
DU → PDR → CRI (specific indirect)	.180	4.709	<.001	[.111, .261]	Significant — H4 supported

Table 6. Mediation analysis: specific indirect effect. Classification: indirect-only (full) mediation (Zhao et al., 2010), since the direct effect (H1) was not significant.

5.6 Predictive relevance

Model fit and out-of-sample predictive relevance were assessed to complement the primarily explanatory analysis above. Table 7 summarises R^2, adjusted R^2, and Q^2predict for both endogenous constructs. SRMR was .046, below the .08 threshold conventionally used to indicate acceptable fit (NFI = .925). PLSpredict (Shmueli et al., 2019) produced positive Q^2predict values for both endogenous constructs (PDR = .142, CRI = .041), indicating the model outperforms a naive mean-based benchmark out-of-sample. The cross-validated predictive ability test (CVPAT; Liengaard et al., 2021) confirmed this formally: the PLS-SEM model produced significantly lower prediction loss than both a naive indicator-average benchmark (average loss difference = -.107, t = 2.465, p = .015) and a more conservative linear-model benchmark (average loss difference = -.038, t = 2.185, p = .030), providing statistical, not merely descriptive, evidence of predictive validity.

Endogenous construct	R^2	Adj. R^2	Q^2predict	Effect size (Chin, 1998)
Perceived Delivery Risk (PDR)	.155	.150	.142	Weak
COD Doorstep Refusal Intention (CRI)	.232	.223	.041	Weak-moderate

Table 7. R^2, adjusted R^2, and out-of-sample Q^2predict for endogenous constructs.

6. Discussion

This study set out to test whether last-mile delivery uncertainty increases customers' intention to refuse a COD parcel at the doorstep, and whether perceived delivery risk explains this relationship. Three of the four hypotheses were supported, and the pattern across all four together produces a more precise theoretical claim than any single hypothesis could on its own.

H2 and H3 confirm the two links in the proposed chain individually: delivery uncertainty is strongly associated with perceived delivery risk, and perceived delivery risk is strongly associated with refusal intention. Both effects were not only statistically significant but comfortably powered (achieved power exceeding 99.9% for each), and both align with the theoretical mechanisms proposed in Section 2 — uncertainty as the informational precondition for risk appraisal (Bauer, 1960), and refusal as a threat-avoidant behavioural response to that appraisal (Rogers, 1975; Maddux and Rogers, 1983). The strong discriminant validity between DU and PDR (HTMT = .415) further indicates that respondents were not simply reporting the same underlying discomfort twice under two labels; the two constructs behaved as theoretically distinct, sequentially related states, resolving — at least within this context — the ambiguity in prior literature over whether uncertainty and risk are separable (Mitchell, 1999; Quintal et al., 2010).

H1, by contrast, was not supported, and this is the more theoretically informative result. A customer's raw exposure to delivery uncertainty did not, on its own, meaningfully predict refusal intention once perceived risk was accounted for (f^2 = .003). Combined with the significant indirect effect (H4), this produces an indirect-only mediation pattern: uncertainty does not appear to drive refusal directly, but only through the cognitive act of appraising that uncertainty as risky. This is a meaningfully different claim from 'uncertainty causes refusal,' and it carries real consequences for both theory and practice, discussed below. It also rules out a simpler, more mechanical story — that customers refuse parcels out of impulsive caution whenever something feels unpredictable — in favour of a more deliberative one, in which the refusal decision is downstream of a specific evaluative judgment about potential loss, inconvenience, or disappointment.

Two caveats temper this reading. First, the null direct effect was estimated with limited statistical power (18.1%) — not because the sample was poorly designed, but because the true effect, if any, is evidently small enough that detecting it reliably would require a sample over ten times larger. The theoretically cleaner interpretation — that the direct pathway is

genuinely negligible — remains the most parsimonious reading of the evidence, but it is not, strictly, unfalsifiable with a larger sample. Second, the model's modest R^2 values (.155 for PDR, .232 for CRI) indicate that delivery uncertainty is one antecedent of perceived risk and refusal intention among others not captured here — plausibly individual risk propensity, generalised trust in the specific seller or platform, or product category risk — a limitation returned to in Section 9.

6.1 What the control variables add

The instrument also collected six variables outside the hypothesised model — order value, product category, seller/platform trust, division, area type, and recalled refusal frequency (Section 4.3; Table 1) — precisely so that plausible alternative explanations for the refusal pattern could be checked rather than assumed away. Supplementary (non-hypothesised, exploratory) analysis found no meaningful association between recalled past refusal frequency and trust (ρ = .032, p = .676), typical order value (ρ = -.078, p = .305), area type (ρ = -.015, p = .841), or online shopping frequency (ρ = .105, p = .164); mean past-refusal counts were also similar across rural (0.90), semi-urban (1.12), and urban (1.00) respondents, and across trust levels (0.89–1.19). This pattern is informative precisely because it is null: it suggests that the refusal behaviour reported in this sample is not simply a proxy for generalised distrust, price sensitivity, or rural infrastructure disadvantage, each of which would be expected to correlate with refusal frequency if it were the true driver. That the strongest, most consistent signal in the data remains the delivery uncertainty → perceived risk → refusal intention chain, and not these background characteristics, strengthens — without proving — the internal-validity case that the psychological mechanism proposed in Section 2 is doing the explanatory work, rather than an unmeasured demographic confound. This check is necessarily exploratory and post hoc, and is reported as interpretive context rather than as a further confirmatory test.

7. Theoretical Implications

This study contributes to theory in three ways. First, it provides empirical evidence — via strong discriminant validity between DU and PDR — that delivery uncertainty and perceived risk are separable constructs at the point of delivery, extending Quintal et al.'s (2010) finding of risk/uncertainty separability in a tourism context into a supply-chain, post-purchase setting where the two states unfold sequentially rather than simultaneously. Second, the indirect-only mediation pattern extends Protection Motivation Theory (Rogers, 1975) into a novel behavioural domain — COD doorstep refusal — and clarifies that within this domain, risk appraisal functions as a necessary, not merely contributing, mechanism linking a threat state (uncertainty) to a protective behaviour (refusal). Third, by locating this mechanism specifically at the delivery stage, rather than at the pre-purchase stage where the large majority of the perceived-risk literature has concentrated (Phamthi, 2024), the study identifies a second, understudied point in the e-commerce transaction at which risk perception has direct behavioural and supply-chain consequences.

8. Practical Implications

The indirect-only mediation finding carries a specific, non-obvious managerial implication: interventions that reduce the visibility of delivery uncertainty without reducing customers' underlying risk perception are unlikely, on this evidence, to meaningfully reduce doorstep refusal. A tracking interface that merely suppresses or delays showing a problem, for instance, may lower perceived uncertainty without lowering perceived risk, in which case refusal behaviour would not be expected to fall. Managers should instead prioritise interventions aimed directly at the risk appraisal itself: proactive, specific reassurance communication when a delay occurs (naming the cause and the resolution, not merely restating a new estimated date), verified order-accuracy confirmation before dispatch, and clearly communicated service-recovery guarantees (free return collection, immediate refund, or replacement) that reduce the customer's perceived financial and functional exposure to accepting an uncertain delivery.

The trust profile in the sample (Table 1) is informative here: trust in sellers/platforms was bimodal — 23.9% reported very low trust and 24.4% very high trust, with comparatively fewer respondents in between — suggesting Bangladeshi COD customers are not a homogeneous population with respect to risk sensitivity, but instead split into a chronically distrustful segment for whom risk-reduction communication may need to be more assertive and specific, and a high-trust segment for whom lighter-touch reassurance may suffice. With just over half of respondents (52.8%) reporting at least one actual refusal in the past six months, this is not a marginal edge case for Bangladeshi e-commerce and courier operators, but a routine, costly pattern of reverse logistics activity that a modest, well-targeted investment in risk communication could plausibly reduce.

9. Limitations and Future Research

Several limitations qualify these findings and point to future research. First, the sample (n = 176) was recruited through convenience and snowball channels with quota monitoring, not probability sampling; while the resulting spread across divisions, area types, and occupations was broad, the sample cannot be assumed representative of Bangladesh's online-shopper population, and results should be generalised with caution. Second, the design is cross-sectional and the dependent variable is self-reported refusal intention rather than observed refusal behaviour; the well-documented

intention–behaviour gap (Sheeran, 2002) means the estimated effects on actual reverse-logistics volume may differ from the effects estimated here on intention. Third, the study is set in a single country and payment context; whether the same indirect-only mediation pattern holds in other COD-dominant markets, or breaks down where COD is a minority payment method, is an open question. Fourth, the model's modest explanatory power (R^2 = .155–.232) indicates unmeasured antecedents of perceived risk and refusal intention remain to be identified; individual risk propensity, seller- or platform-specific trust, and product category risk are plausible candidates future studies could add as controls or moderators. Fifth, and specifically, the low achieved power for the direct DU→CRI path (18.1%) means this study cannot rule out a small true direct effect; a considerably larger sample would be required to test this definitively. Future research could address these limitations through probability or panel-based sampling, longitudinal or experimental designs capable of observing actual refusal behaviour, replication in other emerging e-commerce markets, and the addition of theoretically motivated moderators — for example, testing whether product value or platform trust strengthens or weakens the risk–refusal link identified here.

10. Conclusion

This study aimed to examine whether the uncertainty of the last-mile delivery affects the refusal of a COD parcel at the doorstep among consumers in Bangladesh and also whether the difference in delivery uncertainty explains the relationship between COD parcel refusal at the doorstep. It reveals that the impact of uncertainty on refusal intention is entirely indirect via its impact on perceived delivery risk: uncertainty increased perceived delivery risk, which in turn increased refusal intention, and the effect of uncertainty on refusal intention was not significant once the indirect pathway was considered. In a "cash-on-delivery" supply chain, where refusal at the doorstep has no real consequence until the moment of physical delivery, this is an indirect-only mediation pattern where a failure to deliver can be interpreted as a psychologically explainable, and therefore controllable, point in the reverse-logistics chain where something "might" go wrong rather than simply "will."

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