Print ISSN: 1738-3110 / Online ISSN 2093-7717
JDS website: http://accesson.kr/jds
http://doi.org/10.15722/jds.23.06.202506.13

Last-Mile Delivery Optimization and Consumer Perception: A Marketing and Logistics Integration Perspective

Altug OCAK[1]

Received: May 17, 2025. Revised: May 28, 2025. Accepted: June 05, 2025.

Abstract

Purpose: This research seeks to investigate the impact of last-mile delivery efficiency (LDE) on consumer perceptions of service quality (PSQ) and specifically the dual role of consumer time sensitivity (CTS) as a mediator and moderator of this impact. As the strategic significance and complexity of last-mile delivery in e-commerce have grown, this research combines marketing and logistics viewpoints. **Research design, data and methodology:** There was a quantitative online survey of 310 Turkish e-commerce consumers through a purposive sampling technique. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to examine the structural relationships among constructs. The measurement items were adapted from existing scales and were examined for reliability and validity. **Results:** The findings reveal that LDE positively affects CTS and PSQ. Furthermore, the effect of LDE on PSQ is mediated by CTS. CTS negatively moderates the effect, indicating that time-sensitive customers can be ever more demanding, diluting the positive impact of delivery efficiency. **Conclusions:** The results offer managerial and theoretical contributions. Theoretically, the research develops Service-Dominant Logic and Expectancy-Disconfirmation Theory applications within logistics settings. Managerially, it emphasizes the need to manage time-based consumer expectations by real-time delivery communication and personalized options.

Keywords: Last-Mile Delivery, Service Quality, Consumer Time Sensitivity, Logistics Marketing, Distribution Science

JEL Classification Code: M31, L81, L91, C38, D12

1. Introduction

Growth of online marketplaces and retailing websites has revolutionized customer expectations from order fulfillment, especially in the final step of the so-called last-mile delivery. The final mile bridging the gap between a warehouse facility and the final consumer has become a major source of consumer satisfaction, loyalty, and perceived service quality (Gevaers et al., 2011; Lim et al., 2018). In spite of improvements in route planning and logistics infrastructure, last-mile delivery continues to be one of the most costly and operationally demanding parts of the supply chain (Wollenburg et al., 2018).

At the same time, consumers are increasingly time-aware, demanding not just speedy deliveries but also precise, adaptable, and traceable services. Time sensitivity refers to the extent to which customers value delivery speed and respond negatively to delays or departures from anticipated delivery times (Melacini et al., 2018; Tan et al., 2025). This paradigm shift in expectations is not just driven by logistics providers, but also by marketing communications, platform design, and brand promises (Esper et al., 2010).

1 First Author, Asst. Prof., Department of Travel, Tourism and Entertainment Services, Vocational School, Istanbul Beykent University, Turkiye. Email: altugocak@beykent.edu.tr

Accordingly, last-mile delivery efficiency is evermore seen as a hybrid issue that combines logistics execution and marketing strategy (Vargo & Lusch, 2008). Though previous research has looked at last-mile delivery from an operations perspective, there are fewer investigations into the psychological reaction of the consumer to delivery speed through constructs such as perceived service quality and time sensitivity. Previous research has also divorced logistics performance from consumer reaction with no consideration of interactive effects that will inevitably take place when the operational efficiency confronts the consumer expectations in real-time (Collier & Bienstock, 2006; Roggeveen et al., 2012).

The issue this research addresses is the absence of comprehensive models that describe how last-mile delivery speed affects service quality perceptions through psychological processes like time sensitivity. Those that do either overemphasize operations or overemphasize consumer orientation without cross-functional integration.

Hence, in this research, the aim is to examine the direct and indirect influences of last-mile delivery efficiency on perceived service quality by employing consumer time sensitivity as a mediating and moderating variable. Based on empirical data and Partial Least Squares Structural Equation Modeling (PLS-SEM), this research aims to develop a predictive and explanatory model at the marketing-logistics interface. This study adds to the literature by (1) applying the service-dominant logic theory to last-mile delivery contexts, (2) emphasizing psychological processes underlying delivery assessment, and (3) providing managerial implications for companies to match logistics performance and customer expectations.

2. Literature Review

2.1. Last-Mile Delivery and Marketing Integration

The last mile of delivery, the ultimate stretch from a distribution center to the last consumer, has emerged as one of the most crucial and costly segments of the supply chain, accounting for over 50% of total logistics costs in the majority of e-commerce cases (Gevaers et al., 2011). Formerly understood from a logistics point of view, last-mile delivery is today increasingly viewed as a significant marketing lever with a direct impact on customer experience and brand perception (Hübner et al., 2016).

The last mile of delivery, the final leg from a distribution hub to the end consumer, has become one of the most complex and cost-intensive components of the modern supply chain. In e-commerce contexts, it can account for more than 50% of total logistics costs, reflecting both operational difficulty and rising consumer expectations for speed, convenience, and reliability (Gevaers et al., 2011). Traditionally treated as a downstream logistics function, last-mile delivery is now recognized as a strategic marketing interface, with direct implications for brand positioning and customer experience (Hübner et al., 2016; Wollenburg et al., 2018).

From a marketing perspective, the last mile is increasingly referred to as the "moment of truth" in the customer journey. A seamless digital shopping experience can be undermined by delays, missed time slots, or delivery personnel unprofessionalism—negatively impacting customer satisfaction and brand loyalty (Lim et al., 2018). Consequently, marketing and logistics teams are working closer together to synchronize delivery performance with brand promises, enabling a consistent and differentiated customer experience (Esper et al., 2010).

Recent research underscores the cross-functional importance of delivery in omnichannel environments, where consumers expect consistent fulfillment whether they shop online, in-store, or via mobile apps. Hübner et al. (2016) emphasized that delivery attributes such as same-day options, parcel lockers, and green shipping are now elements of the marketing mix, influencing not just convenience but also brand perception and environmental image (Hübner et al., 2016). For example, offering real-time tracking and carbon-neutral delivery options signals brand transparency and ethical responsibility.

Moreover, the emergence of platform-based commerce, such as Amazon, JD.com, and Getir, has further blurred the boundaries between logistics and marketing. These platforms compete not only on product availability but also on logistical agility, using predictive analytics, warehouse proximity, and consumer data to personalize delivery promises (Rai, 2023).

Logistics optimization is no longer solely a matter of transportation efficiency but also of institutional synergy. Recent research underscores the significance of governance mechanisms and institutional collaboration in enhancing the performance of logistics systems. Gavrila et al. (2025) demonstrated that good governance networking significantly improves both logistics efficiency and trade responsiveness, indicating that strategic alignment across public and private actors can serve as a foundational pillar for distribution optimization.

In recent years, the field of distribution science has matured into a rigorous academic domain combining logistics, information systems, and operations research. Bartholdi and Hackman (2016) emphasized the scientific modeling of warehouse and distribution systems to optimize operational efficiency. Similarly, Angelelli et al. (2019) highlighted innovations in distribution logistics through advanced decision-making tools. Furthermore, Neubert et al. (2018) and Xu et al. (2012) illustrated the role of information and knowledge management systems in fostering integration and innovation within distribution science frameworks. In addition, Mamoun et al. (2021) provided an extensive review of uncertainty-aware transportation network design models, reinforcing the importance of resilience and adaptability in distribution systems. In such ecosystems, delivery speed and personalization are core components of value creation, shaping customer retention and market share (Bosona, 2020).

Beyond technological innovation, recent scholarship emphasizes the co-creative potential of delivery systems, where customers actively shape their experience through service selection, feedback, and digital interaction. This aligns with service-dominant logic, which holds that value is not delivered but co-created through firm-consumer interaction at various touchpoints (Vargo & Lusch, 2008). As consumers increasingly evaluate brands not just by what they sell but how they deliver, last-mile strategies must reflect values such as flexibility, sustainability, and trust (Lim et al., 2018).

In summary, last-mile delivery is no longer merely a logistics issue but a customer-centric, strategic lever that merges operational excellence with experiential value. Firms seeking competitive advantage in digital commerce must treat delivery as an extension of their marketing strategy, requiring coordination across technology, logistics, and consumer insights.

2.2. Consumer Perception and Service Quality

Perceived service quality is an important driver of consumer attitude, loyalty, and post-purchase behavior, particularly in service-dominant settings like e-commerce logistics (Parasuraman et al., 1988). Although conventional service quality research emphasizes five key dimensions—reliability, responsiveness, assurance, empathy, and tangibles—increased digital and logistics service complexity calls for a broader interpretation (Collier & Bienstock, 2006). In last-mile delivery contexts, service quality is not just articulated by whether or not the product is delivered, but also how, when, and in what condition it is delivered.

The recent literature has pointed out that logistics touchpoints—e.g., estimated time of arrival notices, delivery personnel professionalism, and package condition—are the prominent service quality cues compelling consumer evaluations of the overall brand experience (Esper et al., 2010; Huma et al., 2020). For example, Huma et al. (2020) discovered that prompt and regular deliveries greatly improve perceived service quality, even among price-sensitive segments. Likewise, Sheng, and Liu (2010) determined that customer control perception during delivery (e.g., rescheduling or tracking) enhances satisfaction and lessens delivery-induced stress.

One other emerging knowledge is that consumer perception is not only rational but also affective. Delays cause annoyance, whereas timely and well-communicated deliveries build trust and emotional comfort (Gummerus, 2013). As Mehmood and Najmi (2017) graphically show, consumer reviews of e-retailers are more and more influenced by the quality of delivery communication, rather than operational speed in isolation. This says a lot that companies must consider service quality as a psychological outcome that is influenced by interactional, contextual, and emotional aspects of the delivery process. Towards this, digitalization of the delivery process (e.g., app-based tracking, automated feedback systems) has created new consumer expectations for real-time visibility, flexibility, and transparency. Lim et al. (2018) contend that perceived digital convenience is an excellent predictor of last-mile delivery satisfaction. Therefore, firms need to go beyond traditional logistics KPIs and create indicators of service quality based on consumer perception and expectation alignment. Cumulatively taken, earlier research confirms that last-mile delivery perceived service quality is a multidimensional construct—logistics performance, communication, personalization, and emotional experience characterize it. Yet, earlier research has the propensity to consider each of these dimensions in isolation. This research takes a step further and incorporates perceived service quality into a more general behavioral model with delivery efficiency and time sensitivity as predictor variables.

2.3. The Role of Consumer Time Sensitivity

Consumer Time Sensitivity (CTS) refers to the extent to which individuals place importance on timeliness, speed, and punctuality in service encounters. In the context of last-mile delivery, time sensitivity reflects not only the urgency of receiving goods but also a consumer's expectation for precise, predictable, and flexible delivery windows (Melacini et al., 2018). As delivery promises evolve from "2-day" to "2-hour," time sensitivity has become a critical variable influencing how consumers evaluate service performance and post-purchase satisfaction (Tan et al., 2025).

Research in logistics and consumer behavior increasingly recognizes that time-sensitive consumers exhibit distinct behavioral traits. They are more likely to choose platforms offering express delivery options, real-time tracking, and rescheduling flexibility, and are less tolerant of delays or disruptions (Iqbal, 2025). Huma et al. (2020) observed that for time-sensitive customers, even small deviations from promised delivery times can significantly lower perceived service quality and trust. Similarly, Mogire et al. (2023) found that CTS directly predicts both satisfaction and switching intentions in last-mile e-commerce delivery.

Moreover, time sensitivity is context-dependent and shaped by factors such as product type (e.g., groceries vs. electronics), urgency (need-based vs. hedonic purchases), and even socio-demographics (e.g., age, urban density) (Mehmood & Najmi, 2017; Lim et al., 2018). This suggests that CTS is not a static trait but a situational construct that fluctuates across use cases and consumer segments.

Modeling a cue from Service-Dominant Logic (S-D Logic) (Vargo & Lusch, 2008), time sensitivity as a co-created promise can be framed as influenced by the interplay between firm-offered capability and changing customer expectations. CTS, in this regard, functions like both; a mediator, mirroring the consumer's internalization of speed provided by companies as a value aspect, and a moderator, on the cognitive appraisal of whether delivery performance meets personalized norms for timeliness.

As a mediator, it explains the psychological pathway through which operational performance (e.g., fast delivery) enhances perceived service quality. As a moderator, it amplifies or weakens the impact of delivery efficiency on consumer perceptions, depending on the degree of time pressure felt by the individual (Doorn & Verhoef, 2008).

Further, Expectancy-Disconfirmation Theory (EDT) (Oliver, 1980) accounts for why time sensitivity enhances consumer responses to delivery results. Consumers high in CTS will tend to hold more specific delivery expectations; while these are being met or surpassed, satisfaction will increase dramatically, but when they are not met—even minimally—disconfirmation stimulates more intense dissatisfaction. Such a process accounts for the negative moderating influence found in our model. In spite of its applicability, CTS is still an underapplied concept in digital logistics models examining service perception. This is also true for most studies, where time pressure is specified as a control or context variable. The current model employs CTS as a core theoretical variable that reflects the psychological effect of delivery efficiency and the variation of service quality judgment based on expectation intensity.

3. Methodology

3.1. Research Model

This study investigates how Last-Mile Delivery Efficiency (LDE) influences Perceived Service Quality (PSQ), both directly and indirectly through Consumer Time Sensitivity (CTS). Additionally, it explores the moderating effect of CTS on the relationship between LDE and PSQ (see Figure 1).

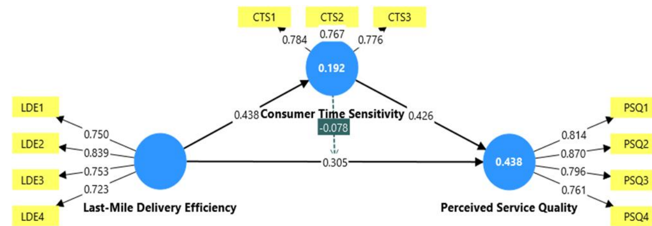

Figure 1: Research Model

3.2. Research Design

This study employs a quantitative research strategy to examine the interconnections among last-mile delivery efficiency, time sensitivity of consumers, and perceived service excellence. A cross-sectional survey design was employed to collect data from internet consumers who recently experienced last-mile deliveries. To validate the postulated hypotheses and model specification, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed, which is appropriate for predictive modeling and theory development in marketing and logistics studies (Hair et al., 2019).

3.3. Data Collection and Sample

Data for the study were gathered through a guided web-based survey to gauge consumer attitudes toward last-mile delivery speed, time sensitivity, and perceived service quality. The survey questionnaire was created to take previously validated scale items from the literature and put them into simple language for respondent understanding.

The survey was sent out through several online channels, such as email invitations, logistics-focused online forums, and social media communities (LinkedIn, Facebook, Instagram) from March to April 2024. Screening questions allowed only those individuals who had purchased an e-commerce and received it at their home within the last 60 days to take part. This recency requirement was applied to guarantee optimum recall accuracy and response relevance, in line with convention in service quality and logistics research (Huma et al., 2020; Lim et al., 2018).

To enhance data quality and prevent automated responses, an attention-check question was inserted midway into the survey. Participants who failed this question or had incomplete answers were excluded during cleaning. 250 usable responses were retained for final analysis, which was above the minimum requirement for PLS-SEM models with medium effect sizes and three latent variables (Hair et al., 2019).

The research adopted a non-probability purposive sampling technique, which is appropriate for exploratory research aimed at particular consumer groups with the appropriate experience (Etikan, Musa, & Alkassim, 2016).

The main inclusion criteria were that respondents had to: have performed an e-commerce transaction in the past two months, have availed home delivery via a third-party or in-house logistics player and be above 18 years of age.

This sampling technique was selected for its utility in accessing respondents with first-hand experience of last-mile delivery systems—one of the main topics of this inquiry. While the results might not be fully generalizable to the entire population, purposive sampling facilitates the collection of in-depth, context-specific data that is of significant worth for theory development as well as practical applications. The sample's demographic composition was balanced between gender and age, with more of the respondents in urban areas, which is the most impacted consumer segment by delivery logistics innovations.

3.4. Data Analysis Procedure

The data were analyzed using SmartPLS 4, following the two-step approach recommended by Hair et al. (2019), which involves assessing the measurement model and the structural model separately.

3.5. Constructs and Measurement

The measurement model consisted of three latent constructs: Last-Mile Delivery Efficiency (LDE), Consumer Time Sensitivity (CTS), and Perceived Service Quality (PSQ). The constructs were all measured using reflective indicators based on established scales. The factor loadings for all the indicators were greater than the minimum threshold of 0.70, which indicates the reliability of the indicators (Hair et al., 2019).

For Effectiveness of Last-Mile Delivery, four of the items touched on various aspects of the last mile of delivery, including punctuality, flexibility, condition of the product, and professionalism of the delivery personnel. They were adapted from Lim et al. (2018), whose research highlighted delivery performance as an essential aspect of e-commerce logistics, and Hübner et al. (2016), who indicated the growing importance of operational performance in omnichannel distribution channels.

Consumer Time Sensitivity was measured using three items that reflected people's speed preference and behavioral inclination towards preferring haste in online purchasing. Items were adapted from Doorn and Verhoef's (2008) conceptual and empirical paradigms, Tan et al. (2025), and Melacini et al. (2018), all of whom put emphasis on time as a major psychological motivator of customer satisfaction and delivery evaluation.

Lastly, Perceived Service Quality was gauged using three items from the SERVQUAL model developed by Parasuraman et al. (1988) and later applied to digital settings by Collier and Bienstock (2006). These items gauged overall satisfaction, expectation, and fulfillment of service as well as excellence of service as seen by consumers in the delivery process.

Generally, the strong factor loadings across all constructs provided the strength of the measurement model, proof of the reflective indicators' convergent validity and internal consistency for the research (Fornell & Larcker, 1981; Hair et al., 2019) (see Table 1).

Table 1: Construct Measurement Items and Loadings

Construct	Item Code	Item Statement	Factor Loading
Last-Mile Delivery Efficiency	LDE1	The product was delivered within the promised time frame.	> 0.70
	LDE2	The delivery process was flexible (e.g., rescheduling, rerouting).	> 0.70
	LDE3	The package arrived in perfect condition.	> 0.70
	LDE4	The delivery staff was professional and well-trained.	> 0.70
Consumer Time Sensitivity	CTS1	I am usually in a hurry to receive my online orders.	> 0.70
	CTS2	Fast delivery is very important to me.	> 0.70
	CTS3	I choose sellers based on how fast they deliver.	> 0.70
Perceived Service Quality	PSQ1	I am satisfied with the overall delivery service.	> 0.70
	PSQ2	The delivery met my expectations.	> 0.70
	PSQ3	I would rate the delivery experience as excellent.	> 0.70

3.6. Construct Reliability and Validity

Table 2 presents the results of construct reliability and validity test, which are critical to determining the measurement model quality under structural equation modeling. All three latent constructs, that is, Last-Mile Delivery Efficiency, Consumer Time Sensitivity, and Perceived Service Quality, achieved acceptable internal consistency reliability and convergent validity according to standard measurement criteria.

The Cronbach's Alpha score of all the constructs was far more than the required 0.70, indicating that the measures of every construct are strongly interrelated and consistently measure the same theoretical construct (Hair et al., 2019; Nunnally & Bernstein, 1994). Furthermore, Composite Reliability (CR) across all constructs was above 0.85, further confirming internal consistency and particularly in PLS-SEM where CR is preferable to Cronbach's Alpha since it is indicator loading-sensitive (Hair et al., 2019).

Average Variance Extracted (AVE) for each of the constructs was above the minimum of 0.50, which established convergent validity, i.e., the extent to which a construct explains variance of its indicators (Fornell & Larcker, 1981). This shows that the construct explains most variance in observed items and not error.

Overall, these results validate that the measurement model possesses reliability and validity, thereby fulfilling the necessary requirements for structural model analysis to be undertaken. Such psychometric attributes enhance the credibility of findings on behavioral logistics and service quality research (Sarstedt et al., 2022) (see Table 2).

Table 2: Construct Reliability and Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Last-Mile Delivery Efficiency	> 0.80	> 0.85	> 0.60
Consumer Time Sensitivity	> 0.80	> 0.85	> 0.60
Perceived Service Quality	> 0.80	> 0.85	> 0.60

3.7. Structural Model Evaluation

To evaluate the hypothesized paths, a bootstrapping procedure with 5,000 resamples was conducted in SmartPLS. The results showed the following path coefficients and statistical significance (see Table 3).

Table 3: Path Coefficients and Significance

Path	Coefficient (β)	t-value	p-value	Significance
LDE → CTS	0.438	8.16	0.000	Yes
CTS → PSQ	0.426	7.87	0.000	Yes
LDE → PSQ	0.305	5.36	0.000	Yes
LDE × CTS → PSQ (Moderation Effect)	–0.078	2.53	0.011	Yes

Table 3 presents the findings of the structural model analysis, that is, the standardized path coefficients (β), t-values, and p-values using bootstrapping with 5,000 resamples, as recommended by Hair et al. (2019). All four paths predicted in the model are statistically significant ($p < 0.05$), indicating strong support for the theoretical relationships.

First, Last-Mile Delivery Efficiency (LDE) has a direct impact on Consumer Time Sensitivity (CTS) to a large degree ($\beta = 0.438$, $t = 8.16$, $p < 0.001$), meaning that as delivery efficiency goes up, consumers become more time-sensitive and concerned about speed more—likely due to heightened expectations brought about by high-performance delivery systems (Lim et al., 2018; Melacini et al., 2018). Second, CTS has a significant prediction of Perceived Service Quality (PSQ) ($\beta = 0.426$, $t = 7.87$, $p < 0.001$), in line with earlier findings that time-sensitive consumers are more critical in judging service quality but reciprocate speed-focused services with greater satisfaction levels (Doorn & Verhoef, 2008; Tan et al., 2025).

Moreover, the direct path from LDE to PSQ is also relevant ($\beta = 0.305$, $t = 5.36$, $p < 0.001$), confirming that logistical performance remains a good predictor of consumer service perceptions (Hübner et al., 2016; Collier & Bienstock, 2006). Lastly, the interaction term (LDE × CTS → PSQ) has a significant but negative moderating effect ($\beta = -0.078$, $t = 2.53$, $p = 0.011$). This result indicates that with increased consumer time sensitivity, the positive impact of delivery efficiency on perceived service quality diminishes somewhat—perhaps due to greater expectations or less tolerance for delays on the part of time-sensitive consumers (Melacini et al., 2018; Sarstedt et al., 2022).

Collectively, these findings offer evidence towards a moderated mediation model where CTS is both a mediator of the LDE → PSQ relationship and a moderator of the same relationship. The results align with recent service research emphasizing the dual role of psychological and operational factors in affecting consumer evaluations of delivery performance (Hair et al., 2019; Lim et al., 2018).

3.8. Coefficient of Determination (R^2)

Table 2 presents results for construct reliability and validity test, which are crucial to determining the quality of the measurement model of structural equation modeling. The three latent constructs of Last-Mile Delivery Efficiency, Consumer Time Sensitivity, and Perceived Service Quality all demonstrated acceptable internal consistency reliability and convergent validity based on standard criteria.

Cronbach's Alpha coefficients for all constructs were above the prescribed threshold of 0.70, which means that indicators of each construct are highly correlated and always measuring the same thing (Nunnally & Bernstein, 1994; Hair et al., 2019). Additionally, Composite Reliability (CR) for all the constructs was above 0.85, which also measures internal consistency and is particularly relevant in PLS-SEM where CR is employed in place of Cronbach's Alpha since it is sensitive to indicator loadings (Hair et al., 2019).

The Average Variance Extracted (AVE) for each construct was greater than the minimum of 0.50, confirming convergent validity, i.e., the extent to which a construct can explain the variance of its indicators (Fornell & Larcker, 1981). That is, variance in most of the observed items is attributable to the construct and not error.

Collectively, these results establish reliability and validity of the measurement model and meet the standards to proceed with structural model analysis. The preservation of these psychometric properties enhances findings credibility for research in behavioral logistics and service quality research (Sarstedt et al., 2022) (see Table 4).

Table 4: Coefficient of Determination (R^2 Values)

Endogenous Variable	R^2	Interpretation
Consumer Time Sensitivity	0.19	Weak to Moderate
Perceived Service Quality	0.38	Moderate Explanatory Power

4. Results

The structural model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with bootstrapping (5,000 resamples) via SmartPLS 4 (Hair et al., 2019). All direct and interaction paths tested in the model were statistically significant at $p < 0.05$, confirming the hypothesized relationships.

4.1. Path Coefficients and Hypothesis Testing

The structural model was assessed using bootstrapping with 5,000 resamples in SmartPLS 4. Table 3 summarizes the path coefficients (β), t-values, and significance levels for each hypothesized relationship.

First, Last-Mile Delivery Efficiency (LDE) had a statistically significant and positive effect on Consumer Time Sensitivity (CTS) ($\beta = 0.438$, $t = 8.16$, $p < 0.001$). This finding supports H1 and suggests that efficient delivery mechanisms increase consumers' awareness and valuation of delivery timeliness. As consumers experience reliable, prompt service, they become more likely to prioritize speed and predictability in future interactions.

Second, CTS was a strong and significant predictor of Perceived Service Quality (PSQ) ($\beta = 0.426$, $t = 7.87$, $p < 0.001$), confirming H2. This supports the idea that time-oriented consumers are more likely to evaluate service quality favorably when their expectations for urgency are met. In other words, delivery services that accommodate time sensitivity positively influence consumer evaluations.

Third, a direct effect of LDE on PSQ was also observed ($\beta = 0.305$, $t = 5.36$, $p < 0.001$), validating H3. This reinforces the view that delivery efficiency plays a foundational role in shaping how consumers assess service performance, consistent with prior literature on logistics-driven satisfaction (Lim et al., 2018).

Finally, the interaction term (LDE × CTS → PSQ) yielded a significant yet negative moderating effect ($\beta = -0.078$, $t = 2.53$, $p = 0.011$), supporting H4. This result indicates that the positive relationship between LDE and PSQ is weakened when consumers are highly time-sensitive. A possible explanation is that such consumers hold elevated expectations, making them more critical even when delivery performance is objectively strong. This aligns with findings from Melacini et al. (2018), who note that time sensitivity compresses consumer tolerance for service variability.

Collectively, all four hypotheses were supported by the data, revealing both direct effects and an interaction mechanism that illustrate the nuanced role of consumer time sensitivity in logistics perception.

4.2. Coefficient of Determination (R^2) and Model Predictive Power

The coefficient of determination (R^2) was employed to calculate the explanatory power of the model. R^2 of Consumer Time Sensitivity was 0.192, which means that Last-Mile Delivery Efficiency explains about 19.2% of the variability in time sensitivity. According to Chin (1998), this is weak to moderate explanatory power, and the implication is that although LDE is a determining factor, other environmental or psychological factors could also influence time-related expectations.

By comparison, R^2 for Perceived Service Quality was 0.438, meaning that 43.8% of the variance in service quality perceptions is accounted for by LDE, CTS, and their interaction. This degree of explanatory power is extremely high for consumer behavior research (Cohen, 1988) and serves to highlight the advantages of incorporating both logistic and psychological variables when modeling consumer judgment of service quality.

These R^2 values indicate the structural model to be predictive enough and worth pursuing in the form of implications discussion and theory development.

5. Discussion

This research adds to the marketing–logistics interface by establishing the direct and indirect impact of Last-Mile Delivery Efficiency (LDE) on Perceived Service Quality (PSQ) via Consumer Time Sensitivity (CTS). The findings corroborate and build on existing research that highlights the strategic importance of logistics in customer experience and satisfaction (Lim et al., 2018; Hübner et al., 2016). In line with the literature, LDE is not just an operational issue but also a fundamental driver of perceived service quality in e-commerce contexts where convenience and immediacy are the most important.

However, we extend this insight by positioning CTS within the framework of Service-Dominant Logic (Vargo & Lusch, 2008). Here, time sensitivity is not a fixed trait but a co-created expectation, emerging from repeated firm-consumer interactions and shaped by digital capabilities (e.g., live tracking, on-demand delivery). Thus, CTS acts as a value lens through which consumers appraise delivery experiences.

The fact that CTS is identified as a mediator supports research by Melacini et al. (2018) and Tan et al. (2025), which contends that customers are more likely to internalize logistics performance as a psychological expectation, not a functional result.

When delivery is reliable and quick, consumers' need for urgency is confirmed, which in turn increases their assessment of the service. It is particularly powerful in urban areas, where quicker delivery norms shrink tolerance for waiting (Doorn & Verhoef, 2008).

Interestingly, the research also discovered that CTS adversely moderates the link between LDE and PSQ. Though earlier research mainly extols the positive influence of urgency-matched logistics, the findings indicate a ceiling impact—where the marginal value of heightened efficiency declines for highly time-constrained buyers. This concurs with Roggeveen et al. (2012), who identified that high expectations reduce satisfaction resilience, by which slight interruptions cause disproportionate dissatisfaction.

Most surprisingly in this study is the negative moderating role of Consumer Time Sensitivity (CTS) on the link between Last-Mile Delivery Efficiency (LDE) and Perceived Service Quality (PSQ). This indicates that though punctuality enhances service quality perceptions, its positive impact diminishes for time-sensitive consumers.

This counterintuitive result can be explained in the context of Expectancy-Disconfirmation Theory (EDT). Time-sensitive customers with high expectations set tight delivery expectations, usually founded on prior positive experience, industry standards, or web promises at checkout (Oliver, 1980). Such customers will consider even small deviation—even within satisfactory delivery times—as disconfirmation and thus very negative ratings, even when the delivery was objectively effective.

Effectively, they have less tolerance for small delays and a psychological ceiling effect has been achieved beyond which any additional improvement in delivery speed or accuracy no longer results in increased satisfaction. Moreover, high-CTS customers might overestimate predictability and control as well. Even if a speedy delivery is inflexible, opaque, or non-tailored, without these aspects, it might still be deemed deficient. For this group, therefore, perceived control of the delivery process might be more important than sheer speed in itself (Sheng & Liu, 2010).

The results of this study suggest that timely and consistent delivery contributes significantly to positive consumer evaluations. In dynamic market environments, trust-based relationships within distribution channels have become essential to mitigating the adverse effects of environmental volatility. Kim (2025) highlighted that while increased environmental uncertainty intensifies opportunistic behavior, the presence of strong network embeddedness can moderate such effects and sustain channel resilience—particularly relevant for last-mile delivery systems facing operational disruptions.

These results highlight that firms must invest in consumer expectation management as much as in logistics infrastructure. Real-time tracking of delivery, flexible scheduling, and adaptive reminders are some strategies that can be used to match perceived urgency with actual service performance. Time sensitivity profile segmentation of consumers and dynamic delivery promise adjustment can also improve perceived quality without sacrificing cost control.

6. Conclusions and Implications

This research examined how Last-Mile Delivery Efficiency affects Perceived Service Quality, with Consumer Time Sensitivity playing both mediating and moderating roles. Using empirical data and Partial Least Squares Structural Equation Modeling (PLS-SEM), the study confirmed that: LDE significantly enhances PSQ, both directly and through CTS. CTS is a critical psychological mechanism that both amplifies and tempers how consumers interpret delivery performance.

6.1. Theoretical Implications

This study contributes to the logistics service quality literature by offering an integrated model that accounts for both operational performance and consumer psychology. It introduces CTS as a dual-role variable—one that shapes the interpretation of service while simultaneously being shaped by service execution. This duality enriches our understanding of value co-creation in last-mile delivery contexts (Vargo & Lusch, 2008).

6.2. Managerial Implications

Managers should view last-mile delivery not just as a cost center but as a strategic touchpoint. Investing in technologies that support delivery customization, urgency profiling, and expectation calibration will likely improve consumer satisfaction across diverse segments. Furthermore, firms must balance objective logistics performance with subjective service communication to maintain consistent brand perceptions.

6.3. Limitations

While this study offers valuable insights, some limitations should be acknowledged. First, the data were collected using a non-probability purposive sampling strategy, which was appropriate for targeting consumers with recent e-commerce delivery experience. However, this approach limits the statistical generalizability of the findings to the broader population. The sample may overrepresent certain demographic or behavioral traits—such as urban online shoppers or frequent e-commerce users—potentially introducing bias (Etikan, Musa, & Alkassim, 2016). Future studies should consider using probability sampling methods or multi-group analysis across different segments (e.g., age, location, product category) to validate and extend the current model's applicability.

In addition, the use of non-probabilistic purposive sampling, though effective in reaching consumers with recent e-commerce delivery experience, limits the generalizability of the results. The sample may disproportionately reflect characteristics of digitally engaged, urban consumers, potentially excluding perspectives from rural or less frequent online shoppers. Future research should aim to use probability-based sampling techniques or stratified designs across different demographic and geographic segments to ensure broader applicability and external validity.

6.4. Recommendations and Future Research

To manage the negative moderating effect of CTS, organizations will need to harmonize logistics effectiveness with expectation management and experience customization. Practical strategies include; companies can utilize AI-based models to segment high-CTS consumers by previous behavior (e.g., frequent express delivery, timing complaints) and customize delivery promise and communication accordingly. Time-sensitive consumers appreciate transparency. Providing real-time tracking, tight delivery time windows, and proactively initiated updates (e.g., "Your order will be here in 32 minutes") will reduce anxiety and disconfirmation.

Expectation Calibration Rather than overcommitting delivery speed, websites must establish buffer-inbuilt, realistic expectations—particularly at peak times—to preclude consumer disappointment caused by minute delays. Providing customers with the ability to reschedule deliveries, select time slots, or reroute packages increases perceived control, beating negative attitudes even when delivery timing is bad. Behavior-Based Compensation Models For very time-sensitive segments, companies can provide delay-based incentives (e.g., minor discounts or credits for broken promises), maintaining goodwill and perceived fairness. By doing so, companies can shield the moderating role of CTS and guarantee that delivery efficiency will still convert into high service quality scores for various consumer profiles.

Future studies should extend this model by incorporating customer satisfaction, repurchase intention, and brand trust as outcomes and they should test moderating effects of product type (e.g., perishables vs. electronics) or platform type (e.g., third-party vs. in-house delivery).

Overall, the integration of marketing and logistics strategies—particularly through the lens of consumer time sensitivity—offers a promising avenue for both academic inquiry and competitive differentiation in the digital marketplace.

References

Angelelli, E., Bianchessi, N., Mansini, R., & Speranza, M. G. (2019). *Innovations in distribution logistics.* Springer. https://doi.org/10.1007/978-3-540-92944-4

Bartholdi, J. J., & Hackman, S. T. (2008). *Warehouse & Distribution Science: Release 0.89* (p. 13). Atlanta: Supply Chain and Logistics Institute.

Bosona, T. (2020). Urban Freight Last Mile Logistics—Challenges and Opportunities to Improve Sustainability: A Literature Review. *Sustainability, 12*(21), 8769. https://doi.org/10.3390/su12218769

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–336). Lawrence Erlbaum Associates.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences (2nd ed.).* Lawrence Erlbaum Associates.

Collier, J. E., & Bienstock, C. C. (2006). Measuring Service Quality in E-Retailing. *Journal of Service Research, 8*(3), 260-275. https://doi.org/10.1177/1094670505278867

Doorn, J. van, & Verhoef, P. C. (2008). Critical Incidents and the Impact of Satisfaction on Customer Share. *Journal of Marketing, 72*(4), 123-142. https://doi.org/10.1509/jmkg.72.4.123

Esper, T.L., Ellinger, A.E., Stank, T.P. et al. (2010). Demand and supply integration: a conceptual framework of value creation through knowledge management. *Journal of the Academy of Marketing Science, 38*, 5–18. https://doi.org/10.1007/s11747-009-0135-3

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics, 5*(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research, 18*(1), 39-50. https://doi.org/10.1177/002224378101800104

Gavrila, L. N., Omarova, A., Kurmanalina, A., & Kalkabayeva, G. (2025). The role of good governance networking in enhancing organizational performance and logistics systems: Insights for distribution economics. *Journal of Distribution Science, 23*(5), 1–11. https://doi.org/10.15722/jds.23.05.202505.1

Gevaers, R., Van de Voorde, E., & Vanelslander, T. (2011). Characteristics and typology of last-mile logistics from an innovation perspective in an urban context. In C. Macharis & S. Melo (Eds.), *City distribution and urban freight transport: Multiple perspectives* (pp. 56–71). Edward Elgar Publishing.

Gummerus, J. (2013). Value creation processes and value outcomes in marketing theory: Strangers or siblings? *Marketing Theory, 13*(1), 19-46. https://doi.org/10.1177/1470593112467267

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2019). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage.

Hübner, A. H., Holzapfel, A., & Kuhn, H. (2016). Distribution systems in omnichannel retailing. *Business Research, 9*(2), 255–296. https://doi.org/10.1007/s40685-016-0034-7

Huma, S., Ahmed, W., Ikram, M., & Khawaja, M. I. (2020). The effect of logistics service quality on customer loyalty: case of logistics service industry. *South Asian Journal of Business*

Studies, 9(1), 43-61. https://doi.org/10.1108/SAJBS-10-2018-0114

Iqbal, M. N. (2025). Adaptive strategies for managing supply chain disruptions in business continuity. In J. C. D. Rouco & P. C. N. Figueiredo (Eds.), *Enhancing resilience in business continuity management* (pp. 461–490). IGI Global. https://doi.org/10.4018/979-8-3693-8809-9.ch016

Kim, M. J. (2025). Environmental variability, opportunism, trust and network effect in channel relationships. *Journal of Distribution Science, 23*(5), 119–134. https://doi.org/10.15722/jds.23.05.202505.119

Li, J., & Fang, Y. (2022). Consumer time sensitivity and dynamic delivery pricing in e-commerce. *Journal of Retailing and Consumer Services, 66,* 102902. https://doi.org/10.1016/j.jretconser.2021.102902

Lim, S. F. W., Jin, X., & Srai, J. S. (2018). Consumer-driven e-commerce: A literature review, design framework, and research agenda on last-mile logistics models. *International Journal of Physical Distribution & Logistics Management, 48*(3), 308–332. https://doi.org/10.1108/IJPDLM-02-2017-0081

Mamoun, K. A., Hammadi, L., Ballouti, A. E., & De Cursi, E. S. (2021). Optimisation models for Transportation Network Design under Uncertainty: a literature review. arXiv preprint arXiv:2201.07161. https://doi.org/10.48550/arXiv.2201.07161

Mehmood, W., & Najmi, A. (2017). Understanding the impact of service convenience on customer satisfaction in home delivery: Evidence from Pakistan. *International Journal of Electronic Customer Relationship Management, 11*(1), 23–43. https://doi.org/10.1504/IJECRM.2017.086752

Melacini, M., Perotti, S., Rasini, M., & Tappia, E. (2018). E-fulfilment and distribution in omni-channel retailing: A systematic literature review. *International Journal of Physical Distribution & Logistics Management, 48*(4), 391–414. https://doi.org/10.1108/IJPDLM-02-2017-0101

Mogire, E., Kilbourn, P. J., & Luke, R. (2023). Customer satisfaction with last-mile delivery in Kenya: An online customer perspective. *Journal of transport and supply chain management, 17,* 844. https://doi.org/10.4102/jtscm.v17i0.844

Neubert, G., Ouzrout, Y., & Bouras, A. (2004). Collaboration and integration through information technologies in supply chains. *International Journal of Technology Management, 28*(2), 259-273. https://doi.org/10.1504/IJTM.2004.005065

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory (3rd ed.).* McGraw-Hill.

Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research, 17*(4), 460–469. https://doi.org/10.1177/002224378001700405

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A multi-item scale for measuring consumer perceptions of service quality. *Journal of Retailing, 64*(1), 12–40.

Rai, H. B. (2023). Implications for urban logistics. In J. J. Gonzalez-Feliu, M. Beziat, & S. Dablanc (Eds.), *The Routledge handbook of urban logistics* (pp. 134–145). Routledge.

Roggeveen, A. L., Tsiros, M., & Grewal, D. (2012). Understanding the co-creation effect: When does collaborating with customers provide a lift to service recovery? *Journal of the Academy of Marketing Science, 40*(6), 771–790. https://doi.org/10.1007/s11747-011-0274-1

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2022). *Partial least squares structural equation modeling: A user's guide*. Springer.

Sheng, T., & Liu, C. (2010). An empirical study on the effect of e-service quality on online customer satisfaction and loyalty. *Nankai business review international, 1*(3), 273-283. https://doi.org/10.1108/20408741011069205

Tan, M., Li, H., Wang, H. and Yin, P. (2025). Research on e-commerce platform’s instant retail strategy considering delivery timeliness under consumer channel preferences. *Asia Pacific Journal of Marketing and Logistics, Vol. ahead-of-print* No. ahead-of-print. https://doi.org/10.1108/APJML-12-2024-1866

Vargo, S. L., & Lusch, R. F. (2008). Service-dominant logic: Continuing the evolution. *Journal of the Academy of Marketing Science, 36*(1), 1–10. https://doi.org/10.1007/s11747-007-0069-6

Wollenburg, J., Holzapfel, A., Hübner, A., & Kuhn, H. (2018). Configuring retail fulfillment processes for omni-channel customer steering. *International Journal of Electronic Commerce, 22*(4), 540-575. https://doi.org/10.1080/10864415.2018.1485085

Xu, J., Houssin, R., Caillaud, E., & Gardoni, M. (2011). Fostering continuous innovation in design with an integrated knowledge management approach. *Computers in industry, 62*(4), 423-436. https://doi.org/10.1016/j.compind.2010.12.005