CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

Research methodology is the systematic approach through which a researcher endeavors to discover and expand upon fundamental comprehension and information regarding a specific subject. It is an investigation of the nature, reasons, and outcomes of specific conditions that are controlled and documented as they unfold (Hair et al., 2007). This chapter aims to explore many viewpoints on research, including data types, research design, data collection methods, and analysis. This section describes the various research methodologies employed to fulfill the research aim. The previous chapters have outlined the study's background by examining the competitive advantages of courier and express service providers in terms of innovation, operational efficiency, resources and capabilities, and customer satisfaction. The study's goal, problem statement, and research objectives have been defined, along with a concise description of the research methodology. The study aimed to examine the adaptability of courier and express services providers in a disruptive environment. The study evaluated CEP service providers in the market to understand customer service experience, expectations, the significance of customer loyalty, and disloyalty. The study offered insight into the index value at the present time and how this value might be used to determine the precise current market position. This chapter outlines research design, research approach, pre-testing of the instruments, reliability testing, validity testing, data analysis methodologies, and software used for survey analysis.

3.2 Research problem

The CEP industry plays a very important role in the transmission of documents and parcels from one place to another and meets the needs of both the general public and business entities. Nowadays, courier and express services are in high demand, and more than 50% of the clients of TSL (transportation and logistics) providers use this service (Switala, 2013). This market is highly fragmented with the presence of several major players like

DHL, UPS, FedEx, Aramex, etc. The local companies are facing high competition from multinational companies that have a comparatively well-developed infrastructure. A number of start-ups are entering the market, and there is a trend of large companies acquiring (or through tie-ups) these start-ups to gain a significant footprint in the market. Competition factor leads to cost reduction and total factor productivity growth in the private sector (Mizutani, 2003). There is a decline in the mail delivery of the Postal system due to changing customer demand, neck-to-neck competition from the operators in the same field, unfavorable business divergence, and substitution of paper mail with digital alternatives (Laseinde et al., 2017). Nolan et al. (2001) examined that the structure of subsidy and the anti-competitive policy of the government negatively affect not just cost efficiency but operational efficiency as well. Though the Postal department has also started responding to some competition factors by developing certain new/premium products to meet the customers' demand but the success is doubtful (David, 2007). By the time they responded to the competitor's entry, private couriers had already captured most of the market share of the department. The revenue deficit of India Post had ballooned nearly 150% from Rs 6,007 crore in FY16, and the losses rose up to Rs 15,000 crore in FY19, replacing Air India, BSNL as the biggest loss-making public sector undertakings (PSUs) (Business Today, April 15, 2019). But it has the widest coverage with 0.15 million post offices across the country. Courier services also reached rural areas, which can be a bigger threat or challenge in the coming years; however, intense competition is mostly found in urban areas (Potdar, 2015).

Apart from internal factors, external factors such as uncertainty and risk affect the organizational performance (Andrejic, 2013; Wang, 2017). The world has witnessed various widespread illnesses and virus outbreaks disrupting various sectors from time to time (Table 3.1).

Table 3.1 Pandemics/epidemics

Epidemic /Pandemic outbreaks	***Year***
Plague	1720
Cholera	1870
Spanish flu	1918
SARS	2003
Swine flu (H1N1)	2009
Ebola	2014
SARS-CoV-2 (COVID-19)	2019

Increasing frequency of this kind of sudden disruption gives an indication to study the preparedness and reactions of the courier and express industry, which may serve as a reference if a similar crisis happens in the future. Despite having an efficient logistics network along with accessible modern technology and experience gained over the years, there is inequality in the ability of the courier, express, and parcel service operators to fulfill the requirements of the customers. Thus, a comparative study of the preparedness of the courier, express, and parcel service providers under an uncertainty scenario is the need of the hour for growth and sustainability in the market.

3.3 Need of the study

In India, the courier and express parcel (CEP) industry plays a critical role in the global economy, directly or indirectly employing 1.6 billion people and contributing significantly to national revenues. The sector generated INR 3,000 crore through service tax and an additional INR 2,000 crore in FY17 from customs duties (Deloitte, 2018). The rapid expansion of e-commerce further amplifies the relevance of CEP services, making them a cornerstone of economic growth by creating employment opportunities and contributing to government revenue.

Private couriers are often lauded for their agility and customer-centricity. However, the postal system faces several challenges, including financial inefficiencies, low productivity, and stiff competition from private players. Technological advancements in communication, especially in the internet and telecommunication, have reshaped the industry, necessitating innovation and adaptability for survival. For a healthy economy, both public and private CEP players must co-exist, leveraging their respective strengths to foster a competitive environment (Warner & Heftez, 2003). Public providers like India Post bring unparalleled reach, while private players excel in service customization and efficiency. Despite their unique advantages, there remains a significant gap in understanding how these providers can effectively address vulnerabilities and enhance performance in disruptive scenarios.

The COVID-19 pandemic underscored the indispensable nature of CEP services. During the nationwide lockdown, when private couriers were largely unavailable, the postal department facilitated the transportation of over 2 crore essential parcels, including medicines, equipment, and raw materials (The Hindu, June 14, 2020). This highlighted the need to measure the resilience of this sector in ensuring supply chain continuity during crises. This study aims to bridge this gap by proposing a competitive preparedness index to evaluate the resilience of CEP service providers.

Although service quality in the CEP sector has been extensively studied using frameworks like LSQ and SERVQUAL, these models fall short of addressing the resilience required in rapidly changing and unpredictable environments. By integrating resilience factors with traditional service quality dimensions, the study provides a robust framework for assessing and improving courier services.

In the face of increasing disruptions, from pandemics to geopolitical challenges, it is imperative to understand and enhance the competitive capabilities and organizational performance of CEP providers. This research offers actionable insights to help both public and private players adapt to evolving market conditions, ensuring sustained service quality, customer satisfaction, and economic contribution. By developing a comprehensive resilience evaluation model, the study not only contributes to academic literature but also provides strategic guidance for fortifying the courier industry against future disruptions.

3.4 Objectives of the study:

1. To identify product/service innovations being implemented by the courier, express, and parcel service providers in times of disruptions.
2. To determine the areas of competitive advantage of the courier, express, and parcel service providers in times of disruptions.
3. To assess the operating efficiency of the courier, express, and parcel service providers in times of disruptions.
4. To determine the factors influencing customer satisfaction levels from courier, express, and parcel service providers in times of disruptions.
5. To develop a framework mechanism for gauging differentiation and competitive preparedness by courier, express, and parcel service operators service providers in times of disruptions.

3.5 Research hypothesis development and conceptual framework

The hypotheses for this study were developed objective-wise (Table 3.2), and a conceptual framework was also developed for courier service quality (Figure 3.1).

Table 3.2 Hypothesis for this study

Objectives	***Hypotheses***
Objective 1	*H1* The introduction of innovation by CEP service providers positively influences business performance during disruptions
Objective 2	*H2* Factors of competitive advantages of CEP service providers positively influence business performance during disruptions
Objective 3	*H3* Operating efficiency positively influences business performance during disruptions
Objective 4	*H4a.* The quality of CEP services positively impacts customer satisfaction during disruptions *H4b* The quality of CEP services positively impacts customer loyalty during disruptions *H4c* The quality of CEP services negatively impacts customer disloyalty during disruptions *H4d.* Customer satisfaction of CEP services positively impacts customer loyalty during disruptions *H4e.* Customer satisfaction of CEP services negatively impacts customer disloyalty during disruptions *H4f.* Customer loyalty is positively influenced by CEP service quality through customer satisfaction during disruptions *H4g.* Customer disloyalty is negatively influenced by CEP service quality through customer satisfaction during disruptions *H4h.* Customer satisfaction of CEP services positively impacts willingness to pay during disruptions *H4i.* Customer loyalty of CEP services positively impacts willingness to pay during disruptions *H4j.* Customer disloyalty of CEP services negatively impacts willingness to pay during disruptions
Objective 5	*H5* There is a significant difference among the CEP service providers regarding competitive preparedness during disruptions

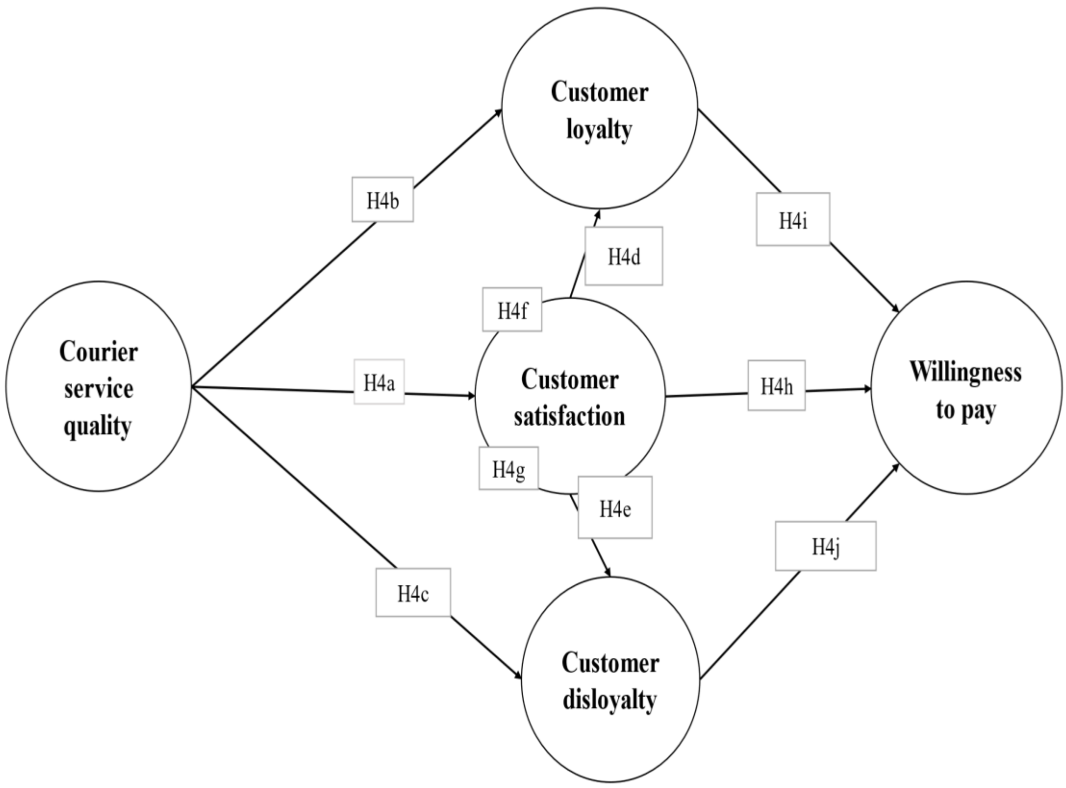


Figure 3.1 Conceptual framework for courier service quality (CSQ) by author(s)

3.6 Scope of the study

3.6.1 Geographic scope

The study would be conducted in Guwahati, the biggest metropolis and the most important city in Northeastern India in terms of its population size, transportation connectivity, and strategic location etc. It is the largest urban concentration with more than 1 million (0.96 million as per Census 2011) out of the total urban population of 4.3 million (Census 2011) in Assam. Being the 'Gateway to the northeast', this city is the hub of economic and commercial activities and gives ample opportunities to courier and express service providers to grow and expand their business in this part of India. Moreover, on 27th August 2015, the central government announced a proposal for the development of 100 Indian cities into 'Smart cities'. Guwahati is one of the twenty cities to be selected in the first round of the Smart Cities Challenge. Thus, there is a great scope of the study in this area, which will help to seek more attention in the national platform and rigorous developmental planning and execution.

3.6.2 Academic scope

While existing literature acknowledges the essential role of LSPs in sustaining service provision, more research is needed to deeply understand the mechanisms they deploy for operational continuity and resilience enhancement during disruptions (Choi, 2021; Gammelgaard et al., 2020; Ivanov & Dolgui, 2020). This study aims to examine and shed light on the reactions and preparedness of CEP in times of sudden disruption of service providers, who serve as critical players within the supply chain, reflecting the broader scope and impact of LSPs. The study identifies the competitive advantages factors and analyzes the operating efficiency of CEP service providers in times of disruptions. This study presents a framework with antecedents and consequences of customer satisfaction in times of disruptions in the CEP industry. Finally, this study measures the CEP industry's resilience against disruption through a composite index and explores the level of competitiveness preparedness among the CEP service providers.

3.7 Research strategy

A research strategy is a systematic plan of action designed to facilitate the proper execution of research. It is beneficial to articulate and recognize the key elements of a study. A research strategy assists in interpreting the identified information and elements to guide the investigation. A research strategy may be qualitative, quantitative, or another type based on the researcher's philosophy. The study utilized a quantitative or deductive approach, employing a standardized questionnaire for data gathering (Saunders, 2016). The quantitative technique is utilized to establish the connection between the constructs. There are three sets of questionnaires in this study. The first group is aimed at individual customers of courier services, while the second set is geared for organizational users of express services. The final questionnaire is intended for service providers. The questionnaires were segmented into many sections according to the study's requirements. The demographics portion included data on age, gender, education, occupation, marital status, and related information. The background information portion included respondents' assessments of the service quality with courier and express service providers. The next portion focused on questions regarding customer satisfaction, consumer loyalty dimensions, customer disloyalty, and willingness to pay. The questionnaire sections assessed customer opinions using a seven-point interval scale. The third set of questionnaires focused on inquiring about service providers' overall operations and organizational performance. A seven-point interval rating scale is once again utilized for this section of the data collection process. The study intends to achieve research objectives by utilizing the primary data collection approach. The diagram illustrating research technique aids in comprehending the key stages of research and its efficacy in examining the correlation between variables to get results (Figure 3.1).

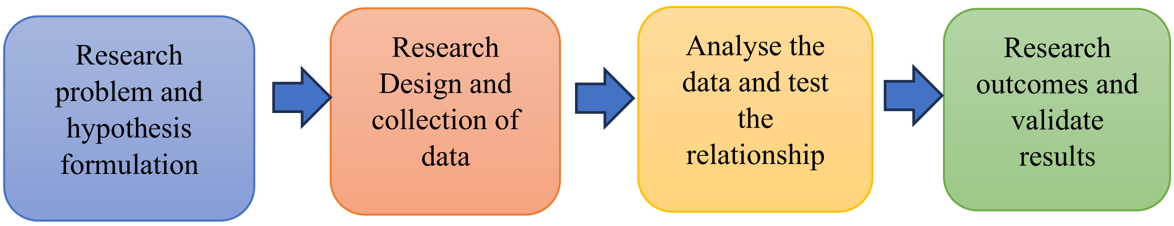


Figure 3.2 Methodological depiction

3.8 Research Design

A research design serves as a template for the study, providing insight into its structure. It details the process of collecting, gathering, evaluating, and interpreting data related to the study goals. The research design aims to establish a comprehensive framework for the study (Hair et al., 2007). Research design can be efficiently implemented by following an organized plan to collect, analyze, and interpret data, as shown in Figure 3.2. The literature review provides an understanding of the problem statement and assists in formulating the hypothesis. After reviewing the literature and identifying the problem, primary research is undertaken using different methods. At the beginning, pilot testing involves analyzing the demography and background of a subset of the sample to assess its dependability before commencing the final testing phase. Final testing involves analyzing data using demographic features, background analysis, inferential, and exploratory analysis, which are then confirmed using validity and reliability tests.

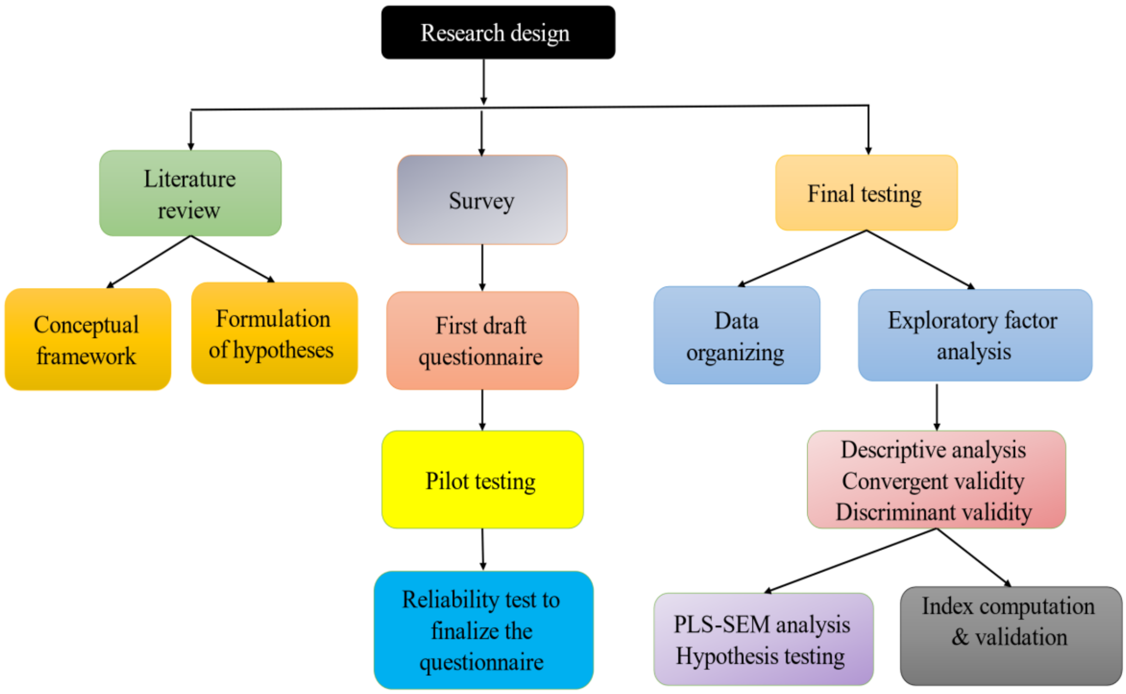


Figure 3.3 Research design framework

This empirical study employs both exploratory and descriptive research designs to collect and analyze data. Initially, exploratory research was conducted to investigate logistics resilience management and assess the preparedness of CEP service providers. This phase involved a comprehensive literature review and informal discussions with CEP managers to gain insights into industry challenges and strategies. The study then adopted a descriptive approach to collect quantitative data, which enables a logical, systematic understanding of resilience in the industry by gathering data from a larger population sample. Primary data for the dependent, independent, and mediator variables was collected through a structured questionnaire administered to CEP service providers and customers, while secondary data was gathered from individual websites and industry reports on the courier and express sector. Based on insights from exploratory research, a causal research design was employed to test the relationships between the identified variables. A structural equation model (SEM) was developed to analyze cause-and-effect relationships among the constructs. Finally, a data-driven composite index formulation was applied to quantify resilience and preparedness, offering a comprehensive, data-based assessment of the industry's readiness for disruptions.

3.9 Sampling Design

3.9.1 Population

For objectives 1, 2, and 3, the population constitutes all the CEP service providers operating at Guwahati and registered with the Guwahati Municipality Corporation as courier service providers

For objectives 1 and 4, the total number of customers availing the services from the CEP service operators (including post offices) in Guwahati.

For objective 5, information gathered from CEP service providers and customers is considered.

3.9.2 Type of Data

Primary data is used for further data analysis.

3.9.3 Data collection method

Table 3.3 Data collection method

Objectives	Methods		
2, 3	Structured questionnaire and interview	Regional, zonal, or branch offices of CEP service providers Heads or High-level managers-operational and logistics managers	
4	Survey method with a structured questionnaire	Sampling Unit- Households and organizations	Sampling Element- Individuals and organizations who use both postal and courier services
1	Structured questionnaire and interview	From both CEP service providers and customers, as mentioned above	

The researcher expects to adopt appropriate data collection methods under these difficult and testing times, possibly through telephonic interviews and/or digital methods to collect data from the respondents, and in some cases, in-person interviews will be done as per the requirements of the study.

***3.9.4 Area of the study**:* The study is conducted at Guwahati, which is situated on the southern bank of the river Brahmaputra, the only megacity in the northeastern region and a commercial and economic hub with a population above 1 million.

3.9.5 Sample Selection:

Objectives 1, 2 & 3:

A census survey is attempted as the list of service providers is limited. The list of CEP service providers is given in Table 3.3 based on Express Industry Council of India (EICI), Courier Association of India, own observation during field visits, and the data from the Guwahati Municipal Corporation (GMC).

Table 3.4 Courier, express, and parcel service providers considered for this study

Private CEP service providers				Public sector
Airex logistics and express services	Ecom Express	Merchant Logistics	Shadowfax	India Post
Akash Ganga Courier	Ekart	Mini Transport	Shiv Shakti Express carriers	
Aradhya Transport	E-tash deliveries	Network Courier	Shree Durga Courier	
Arindam Courier Service	Fedex	North-east courier services	Shree Maruti Courier Service Pvt. Ltd	
Asian International	Flyking Courier Services	OM Logistics Ltd	Shri Tirupati Courier	
Assam Express Courier Services	Gati	Om Sri sai courier	Sky King Courier	
Bharati Express	Goodluck Courier	OneX Deliveries	Speed express	
Blue Dart DHL	Amazon logistics	Purbanchal Courier Cargo Service	Swastik Courier	
Blue Hills Courier	Instakart Service Pvt. Ltd	Radhika Express Service	Swift courier & cargo	
Blue Sky Express Courier	Internal Express	Roadbot	The Professional Courier	
Delhivery Pvt Ltd	Loadshare	Rudraksh Express Service	Trackon Courier Services	
DTDC		Safexpress	XpressBees	

Data was collected from the regional hubs, zonal offices, or branch offices of private couriers and departmental offices (Circle office, Head offices, and sub-post offices) in the case of the postal department.

Objective 1 & 4:

Geographical location:

The Guwahati Municipal Corporation (GMC) is the local government for governing, developing, and managing the city. While the Guwahati Metropolitan Development Authority (GMDA) is another section established for the planning and development of greater Guwahati under the GMDA Act, 1985. The Guwahati Master Plan- 2001 had divided the areas into nine units called the planning units. In the 'Master Plan for Guwahati Metropolitan Area (GMA) 2025' by GMDA, planning unit-1 of 2001 has been subdivided to distinguish between core areas and extended areas. The existing GMA-2025 has 10 planning units (excluding 3 units of the proposed three new towns) as given in Table 3.4.

Table 3.5 Classification of Guwahati city as per GMDA

Planning units	***Area covered***
PU 1	Old Municipality area
PU 2	Hatigaon- Basistha- Khanapara Area
PU 3	Hengrabari-Satgaon Area
PU 4	Narengi- Bonda Area
PU 5	Dipor bill- Fatashil Hill Area
PU 6	Pandu - Maligaon Area
PU 7	Jalukbari - University Area
PU 8	Azara- Borjhar Area
PU 9	North Guwahati- Amingaon Area
PU 10	Extended Area of old Municipality

For identification and selection of sampling elements for customers' survey further division of the city has been done. GMC area, GMA-2025 and previous studies (Mahadevia et al., 2014; Alam 2011) about Guwahati have been considered. The places are classified based on Pincode by India Post under four categories namely core commercial centers, composite areas and areas within PU 8 & 9 along with places outskirts of the Guwahati Metropolitan Area (Table 3.5).

Table 3.6 Pincode-wise distribution of areas of Guwahati and the remaining parts of Kamrup Metro

Core commercial centers	***Composite areas (Residential and/or Commercial)***		***Areas within PU 8 & 9***	***Outskirts of Guwahati city***
781001 (Machhkhowa -Fancy bazaar- Panbazar- Uzanbazar area)	781001 (remaining residential area)	781019 (Kahilipara area)	781015 (Borjhar area)	782402 (Sonapur area)
781005(Dispur)	781003 (Shilpukhuri area)	781020 (Noonmati area)	781017 (Azara area)	782403 (Khetri area)
781006 (Ganeshguri area)	781004 (Kharguli)	781022 (Khanapara area)	781031 (Amingaon area)	781023 (Amerigog)
781007 (Ulubari area)	781006 (Assam Sachivalaya area)	781025 (Ambari Fatashil)	781030 (North Guwahati)	781125 (Mirza area)
781008 (Paltanbazar area)	781007 (Lachitnagar area)	781026 (Narangi area)	781039 (IIT Guwahati)	781132 (Bhagawatipara)
781021 (Bamunimaidam area)	781008 (Rehabari area)	781027 (Satgaon)		781150 (Chandrapur)
781024 (Zoo road area)	781009 (Bharalumukh area)	781029 (Bashistha area)		782401 (Digaru)
781028 (Beltola area)	781010 (Kamakhya)	781032 (Indrapur area)		
	781011 (Maligaon-Gotanagar area)	781034 (Odalbakhra)		
	781012 (Pandu-Adabari area)	781035 (Garchuk area)		
	781013 (Jalukbari area)	781036 (Hengerabari area)		
	781014 (Gauhati University Area)	781037 (Panjabari area)		
	781016 (Gopinath nagar)	781038 (Hatigaon area)		
	781018 (Binovanagar)	781040 (Saukuchi area)		
		781171 (Udyan Bihar area)		

**Names are just to give a general idea about the locality and not the exact area coverage under the Pincode*

3.9.6 Sampling technique

Judgmental sampling will be employed to select the sample for this study. The target population comprises customers who have utilized both postal services and private courier services at least twice during the period from 2020 to 2022. Both individual and organizational users meeting these criteria will be considered for inclusion. This sampling method ensures the selection of respondents who are well-acquainted with the operations and service quality of both public and private CEP providers, enabling a comprehensive evaluation relevant to the study's objectives.

3.9.7 Sample size

The approach "Average sample in similar studies" is used to determine the number of respondents to measure the satisfaction level of the customers. The average of samples taken in the mentioned studies (Table 3.6) is 533.

Table 3.7 Previous studies on customers in courier/LSP/last-mile

Authors	Study	Sample
David (2007)	Measured the success of marketing and promotion of postal services to meet the needs of specific segments of customers	350
Selvakumar (2007)	Customers' perception of the service quality of the courier service operators.	500
Hemalatha (2010)	Customer satisfaction with premium products of the Indian Postal Services	700
Valarmathi (2010)	Studied the factors impacting consumer preference towards courier service	500
Valaei et al., (2016)	Assessed the overall service quality of the courier service industry and the moderating impact of age, gender, and ethnicity	561
Gulc (2017)	Courier service quality	228
Otsetova & Dudin (2017)	Analyzed the courier market in Bulgaria	700
Lasisi (2018)	Emerging issues surrounding the same-day delivery of courier services	1185
Lai et al. (2022)	Customer satisfaction with parcel locker services in last-mile logistics	321
Masudin et al. (2022)	Quality of logistics services during the COVID-19 pandemic: Evidence from Indonesia	289
	Average of the samples	**533**

A minimum sample size of 300 or more was found to be appropriate by some researchers to get a close approximation of population characteristics by performing statistical tests like multiple regression, analysis of covariance, etc., for more rigorous impact evaluation. (Bujang et al., 2017; Israle, 1992). The widely accepted value for a large sample is 30 (Field 2013), whereas some suggest a sample size of 100 or more would make it 'reasonable to use statistics that assume a normal distribution' (de Vaus, 2002).

Thus, considering the above discussions, a sample size of 800 is proposed and found reasonable for the study. Out of which 756 responses are found to be usable.

3.9.8 Sample distribution:

Depending on various segments of customers (individuals and organizational users) and types of CEP services, a 2x2 matrix of sample distribution of the collected samples is given below:

Table 3.8: Sample distribution

CEP user segments		***Sample***
Individual Users of Postal Services	Individual Users of Private CEP Services	408
I	II	
Organizational Users of Postal Services	Organizational Users of Private CEP Services	348
IV	III	
Total		**756**

During sample collection, emphasis was given on the area distribution provided in Table 3.5 to get an appropriate representation of the population.

3.10 Research variable

The variables considered for this study are presented in Tables 3.9, 3.10, and 3.11 for service providers, individual customers, and organizational customers, respectively.

Table 3.9 Variables considered for CEP service providers

Variables	**Sources**
Accurate delivery (Delivery performance)	Cagliano *et al.,* (2017)
security during transit	Laseinde & Mpofu (2017)
Less number of rejected/undelivered items	Hsiao, (2010); Rantasila & Ojala, (2012)
Notifications and alerts for accurate delivery status	
Timely and reliable pickup/delivery (Scheduling /vehicle routing)	Gunasekaran et al (2004)
Flexibility in operations	Sabahi et al., 2020
Ontime express or time-sensitive deliveries	Liu et al., 2018
Short processing time and in transit time	Selvavinayagam *et al.,* 2018
Cost-effective services	Kim 2010
Short response time for queries and conflicts	Choudhury et al., 2018
Delivery agent's efficiency	Arvidsson et al., 2013
Technological advancement	Deng & Noorliza, 2023
Novel delivery solutions or services	Dovbischuk, 2022
Adapted operational processes	Marchet et al., 2017
Advancement in organizational process	Sabahi et al., 2020
Adaptability	Ivanov & Dolgui, 2020
Alignment	Wu et al 2006, Bang et al., 2012
Agility	Bi et al 2003
Geographical coverage	Gunasekaran et al (2004)
Distribution centers and mode of transportation	Min et al., 2015
Resource utilization	Markovis-Somogyi et al., 2011; Wieland & Wallenburg 2013
Collaborations	Zhu *et al.,* 2017; Wieland & Wallenburg 2013
Uncertainty/Risk management	Singh et al, 2020

Variables	**Sources**
Efficient Human resources	Bottani et al., 2015
Sales growth	Wu et al 2006; Chen et al., 2019
Market reach	Tseng & Lian, 2015; Shou et al., 2017
Profitability	Wu et al 2006; Shou et al., 2017
Customer satisfaction	Wieland & Wallenburg 2013; Deng & Noorliza, 2023

Table 3.10 Variables considered for individual CEP service users

Variables	**sources**
Cope with the changes brought by the disruption *Adapt to the disruption easily* *Ability to provide quick response to the disruption* *Maintains high situational awareness during disruptions* *Facilitates home pickups if desired by customers* *Arranging services for containment areas*	Ambulkar et al., 2015; Chunsheng et al., 2020; El Baz & Ruel, 2021
OTP based transaction *Mobile applications, GPS tracking* *Digital/online payment*	Ul-Hameed et al. 2019, Uvet, 2020
Easy adequate information *Short response time* *Customer support system* *Update on shipment status* *Immediate notification on delivered shipment* *Knowledgeable staffs*	Rafiq & Jaafar, 2007: Gupta et al, 2022
Adequate delivery time *Special care for shipments* *Real-time information* *Undamaged shipment* *Fast delivery process* *Make changes in delivery dates and destination*	Mentzer et al., 2001; Andersen et al., 2009; Ho et al., 2012
Confidentiality and privacy *Advance information before actual delivery* *Delivery executives' performance* *Convenient working hours* *Convenient location* *Uniform services*	Chan et al (2006); Purohit (2017); Thai, 2015
Customer's feedback *Information sharing* *Exchange ideas with customers*	Liu & Lee, 2018
Inform delays *Resolve problems promptly and appropriately* *Compensation for damages/loss*	Mentzer et al. 2001; Andersen et al, 2009
Demonstrates creativity *Searches for novel approaches* *Quick to introduce new services*	Restuputri et al, 2020; Huo et al. 2008

Variables	sources
More service availability than competitors Reasonable price than competitors Better service quality than competitors More adaptive to disruptions as compared to competitors	Subramanian et al., 2014
Best service quality despite disruptions Safe and secure despite disruptions Offer promised service despite disruptions Meet my expectations despite disruptions This courier has everything I need to receive/send parcel during disruptions	Kim and Kim, 2016; Phan et al. 2021; Uzir et al., 2021
Continue to use the services in future Recommendation to others Service preference	Kyle et al., 2010; Slack et al. 2020
Will use other service provider if that offer more attractive prices Will pay higher price to competitors because of the service quality Will switch to a competitor if encountered more problems Will certainly voice my concerns, if encounters any issue	Slack et al. 2020
Willingness to pay	
Disruption preparedness	

Table 3.11 Variables considered for organizational CEP service users

Variables	Sources
Accommodates changing and urgent requirement during disruptions Clear, accurate online real-time tracking information Safety assurance Convenient operating working hours Provides automated reports for failed deliveries Efficiently handles shipments during Peak seasons Ensures timely and effective handling of trade documents	Ali et al., 2022; Thai, 2008; Gil Saura et al., 2018
Application of modern updated information technology Delivery confirmation through using modern technology IT application and easy information sharing	Jamkhaneh et al., 2022
Makes arrangement for most of our shipping requisitions Multiple mode of shipments available based on requirement Ease of return from our customers Widespread distribution coverage Upgrading their express delivery time (such as next-day or even same day) Undeliverable shipments handling Assurance of sanitization and adherence to pandemic protocols Contactless delivery for the customers/receiver Availability of alternative delivery options Safely handling and proper communication of shipments trapped mid-shipments during disruptions Provide information on health status of delivery executives to share with customers	Masudin et al., 2022; Valaei, 2016; Jain et al., 2017; Chunsheng et al., 2020
Easy to booking, schedule pickup by phone or web application Provide appropriate and sufficient capacity for desired shipments Provide an option for preferred time slot service for delivery or pickup (such as early morning within 10:30 am or as requested)	Gulc 2020; Tontini et al., 2017

Variables	Sources
The entire logistics process is well coordinated and functioned complying	
Accurate information on current shipment location and the estimated delivery time	Valaei, 2016; Gulc 2020; Ali et al., 2022
Web based order handling, modern packaging solutions	
Shipments send by us delivered at promised time	
Provide information that the package has arrived at the nearest hub	
Communicates through encrypted system that keeps our customer's contact details secure	
Delivery executives perform their jobs well	
Ask for customer's feedback regarding service experience	Liu & Lee, 2018
Informs us when the shipment gets delivered to the end customer	
Keeps us informing about changes, special discounts, offers, new products and services	
Timely processing is done while dealing with the grievances	
Shipping problems are resolved promptly through representative over the phone /internet communications (such as email)	
Take the responsibility in case of damage or loss	
Shipments can be sent to any location as compared to competitors	Subramanian et al, 2014; Jain et al., 2017
Reasonable prices and rates are charged for service as compared to competitors	
Service Quality is better as compared to competitors	
More adaptive to disruptions as compared to competitors	
Delighted to use the services of our courier service providers	Masudin et al., 2022, Uzir et al., 2021
Satisfied with the overall service quality of the courier service providers	
Satisfied with the management and employees of the courier service providers	
Satisfied with the process/ operation of the courier service providers	
Some of business to competitor who offer more attractive prices	Slack et al., 2020
Pay higher price to competitors if I get quality services	
Switch to a competitor if encountered more problems	
Complain to employees and other customers if I encounter service failure	
Outsource more activities and will continue the relationship with our present courier service providers as long as possible	Khan et al., 2020
Recommend our courier service providers to other organization	
Whenever need to send any shipment, prefer this courier service	
Willingness to pay	
Disruption Preparedness	

3.11 Questionnaire development

The tool used in this study is a structured questionnaire developed with a seven-point interval scale to measure service quality and disruption preparedness among two customer groups, individual and organizational users, as well as CEP service providers.

To capture relevant data from the customer groups, two separate sets of questionnaires were designed, tailored to individual and organizational users' needs. For individual users, the questionnaire was divided into two sections. The first section focused on assessing the core variables of the study model, related to the service quality of courier providers. The second section gathered demographic information, including gender, age, education, and income. Additionally, individual customers were asked two separate questions, one on their willingness to pay more than the standard price for improved delivery services and the other on preparedness of the CEP service providers during disruption. The questionnaire for organizational customers also consisted of two sections. The initial section assessed the latent variables of the model, gauging their experiences with service quality. The second section collected demographic details such as gender, age, education level, industry type, position level, and local pin code. Organizational customers were also asked about their willingness to pay more for enhanced delivery services.

For CEP service providers, the questionnaire was similarly structured into two sections. The first section contained questions aimed at evaluating the organization's preparedness during disruptions, while the second section collected demographic information on respondents, including their level of management, years of experience, number of employees, and years of operation.

This methodically designed questionnaire ensured comprehensive data collection across all respondent categories, providing insights into service quality perceptions, disruption preparedness, and the potential for premium service offerings in the courier industry.

3.11.1 Measurement

Objective 1 refers to the critical examination of the products/services that are added to the basic product line by courier and express service providers to meet the demands of the dynamic environment.

Objective 2 is about determining the factors of competitive advantages and detailed analysis to figure out the most important resources/capabilities or value additions that would help the service providers to sustain in the market. The source of high returns in resource-based view is the unique resources, capabilities and knowledge of a firm; that of market-based view is the bargaining power in the market; and the reason as per relational based view is the shared knowledge and resources (Wang, 2004). So, there is no specific way to determine a firm’s competitive advantage, probably a combination of all these views can give a better idea about the competitive advantage (Wang, 2014).

Objective 3 refers to the productivity analysis of the service providers to map out whether the resources are being utilized efficiently and effectively. There has been an increasing demand for the measurement of productivity, more specifically, efficiency. Measurement of efficiency will be attempted for quantification of differentials that are qualitatively predicted by theory.

Objective 4 deals with the evaluation of the functioning of CEP service providers from the customers' perspective. Analysis of customers' satisfaction, needs, and expectations is important to flourish in the market. To achieve this objective, the users will be asked questions regarding the service quality, perceived satisfaction, and behavioral intentions.

Objective 5 is to suggest a framework for CEP service providers based on current market analysis on competitiveness of each player in the industry and the gap between supply-side (service operators) and demand-side (customers) to explore new avenues for the revival of the weak ones and sustainability of the existing service providers and the new entrants. This objective will be attempted by computing composite indices to quantify resilience.

3.11.2 Pilot study

Before initiating the main data collection, an initial evaluation of the data collection tool was carried out to determine its dependability. For the questionnaire pretest, information was gathered from each CEP user. To ensure that the participants understood the instrument sufficiently, the quantitative approach was used (Antwi et al., 2022). The pretest comprised a total of 100 individual customers. This made it easier to simplify some of the questions, and it also helped to eliminate those with low Cronbach alpha coefficients. In total, forty variables related to service quality were included in the final questionnaire used in the study. Additionally, there were five questions on specific factors related to customer satisfaction, three questions about loyalty, four questions about disloyalty, and one question measuring willingness to pay for postal services. Another pretest was conducted with 65 organizational CEP users. The final questionnaire included forty-three service quality variables and eight factors related to customer satisfaction and loyalty. The data so collected were tested for their reliability using Cronbach's alpha, with each value above 0.7.

In addition, a discussion was done with four CEP service providers to get adequate information about how the operations are carried out during disruptions pandemic. It was an unstructured interview as the prime aim was to make a note of the key factors that would be crucial for the study.

3.12 Data collection

Data collection for this study involved two groups: CEP service providers and customers (individual and organizational) who had used both public and private courier services during the two years of pandemic-related disruptions.

For data from CEP service providers, key personnel such as operations managers, regional managers, hub in-charges, and other relevant employees were contacted. They were asked a series of questions to assess their organization's preparedness in times of disruptions. A total of 48 responses were obtained from CEP service providers registered with the Guwahati Municipal Corporation.

For customer data, both offline and online methods were used to distribute questionnaires. A total of 500 questionnaires were collected from individual customers who had used both public and private courier services within the stated period. However, some responses were incomplete or lacked engagement and thus were excluded, resulting in a final dataset of 408 responses. Similarly, 500 questionnaires were distributed to organizational customers, and after removing incomplete and disengaged responses, 348 were retained for analysis.

3.13 Data analysis tools and techniques

This chapter quantitatively analyzed the data acquired from primary sources. The data gathered from different customer and service provider segments through surveys was examined. The section commences with a study of their demographic characteristics. This chapter evaluates the appropriateness of the data and examines certain assumptions that must be met before conducting any statistical analysis. Factor analysis is used to assess the efficacy of each statement. Structural equation modeling was used to meet the study's requirements. Finally, the study hypotheses were examined.

3.13.1 Testing assumption

Prior to conducting any statistical analysis, it is essential to first assess the suitability of the data. The data collected from the questionnaire is examined for assumptions such as normality and multicollinearity. The study was carried out using SPSS and SmartPLS, and it verified that there were no errors in the data related to any of these assumptions.

3.13.1.1 *Normality:* Statistical analyses rely on the normality assumption, assuming that the data adheres to a normal distribution. Skewness and kurtosis are important measurements used to assess deviations from a perfect normal distribution (Groeneveld & Meeden, 1984; Cain et al., 2017; Spencer et al., 2017), which is uncommon in real-world datasets. Skewness measures the asymmetry of a distribution, where a value of zero represents perfect symmetry. Positive skewness indicates a tail extending to the right, whereas negative skewness indicates a tail extending to the left. Kurtosis quantifies the tails of a distribution. Skewness and kurtosis values less than ±3 indicate no heavier or lighter tails, respectively (Groeneveld & Meeden, 1984; Cain et al., 2017). Although these measurements offer vital insights, it is important to acknowledge that minor variation in normality is not a matter to worry about, particularly with larger sample numbers (Field 2013; de Vaus, 2002) or when using strong statistical tests.

3.13.1.2 *Multicollinearity:* Multicollinearity, which arises when predictor variables in a regression model are highly interrelated, has the potential to render estimates unstable and increase regression coefficient variance. It is commonly identified utilizing the variance inflation factor (VIF) and correlation matrix analysis. VIF measures how much the variance of a predictor's coefficient is increased by its correlation with other variables; a VIF of 1 indicates no multicollinearity, implying no correlation with other predictors, whereas values between 1 and 5 indicate moderate correlation, which is usually not a problem. VIF values greater than 5 indicate strong correlation, which may necessitate intervention, while values greater than 10 indicate severe multicollinearity, which might compromise model reliability (Hair et al., 2012). Meanwhile, the correlation matrix provides an initial look at pairwise interactions between predictors; correlations greater than 0.7 or 0.8 may suggest the presence of multicollinearity (Hair et al., 2019a). While large pairwise correlations alone do not prove multicollinearity, they do identify regions for additional examination using VIF. Using VIF and correlation matrix analysis combined allows for the effective identification and mitigation of multicollinearity, whether by deleting, merging, or altering variables.

3.13.2 Reliability and validity

Subsequently, a reflective measurement model evaluation was conducted to verify the reliability and validity of the measurement scales for twelve dimensions, which were established following an exploratory factor analysis (EFA). The outer loadings should exceed the recommended threshold of 0.7 (Hair et al., 2012). Cronbach's alpha above 0.6 indicates internal consistency reliability for a new scale, as stated by Hair et al. (2019a). The average variance extracted (AVE) of all constructs needs to be higher than 0.5, indicating that the measurement scales have adequate convergent validity.

Composite Reliability (CR): The outer loadings should exceed the recommended threshold of 0.7. Cronbach's alpha value should also be above 0.7. This discovery validated the notion that the measuring scales provide a sufficient level of internal consistency reliability for a new scale, as stated by Hair et al. (2019a).

Convergent validity: The relationships between measures of a construct are evaluated by convergent validity. The average variance extracted (AVE) of all constructs was higher than 0.5, indicating that the measurement scales have adequate convergent validity (Hair et al., 2012).

Discriminant Validity: The goodness of fit is a measure that quantifies the difference between the observed values and the expected values of the model. All the constructs in this investigation demonstrated satisfactory discriminant validity according to the Fornell-Larcker criterion. This was determined by evaluating the absolute value of the correlations between the constructs and the square root of the average variance extracted (AVE). The cross-loading results, similar to the Fornell-Larker criterion, should be below 0.1 to demonstrate that all the constructs have discriminant validity (Chin, 1998). The Heterotrait-Monotrait ratio of correlations (HTMT) is employed as a means of assessing the validity of the measurement constructs. The HTMT values are greater than 0.85 (Hair et al., 2012).

3.13.3 Exploratory factor analysis

The study includes nine service quality components analyzed using principal component analysis with varimax rotation as the extraction method for factor analysis. Variables were included in factors based on factor loadings over 0.5, and factors with eigenvalues above

1.0 were kept in the factor analysis. The next phase involved evaluating the communality of each variable to determine which item loadings are significant for interpreting the factors. The communality of the variable, indicating the proportion of variation explained by the factor solution for each variable, was evaluated to confirm satisfactory levels of explanation. The results indicate that the communalities of variables exceeded 0.50 (Hair et al., 2019b). Prior to analyzing the factors, it is essential to assess the data's applicability using the KMO, Bartlett test, and anti-image correlation matrix. KMO must exceed 0.7 (Hair et al., 2019b). The Bartlett's test should yield a significant result ($p < 0.5$), suggesting that the variances of the samples are identical. Both of these tests yielded substantial findings. SPSS was used to extract the factors. Table… presents the number of factors extracted along with their respective variances.

3.13.4 Structural equation modelling

According to the recommendations of Anderson and Gerbing (1988), structural equation modeling (SEM) was used as a two-stage data analysis approach in this work. In the field of behavioral research, SEM has become a standard method of data processing (Zhou et al., 2021). Construct validity, convergent validity, and discriminant validity were initially checked on the outer model, or measurement model. To examine the interrelationships between the explanatory and explanatory variables, we next assessed the internal model, or structural model. To conduct these analyses, we used SmartPLS 4.0 to conduct partial least square structural equation modeling (PLS-SEM). In terms of resilience to collinearity and data distribution, variance-based PLS-SEM is regarded as superior to covariance-based SEM, as stated by Cassell & Bickmore (2000). These two shortcomings of multiple regression can be avoided with PLS because it is nonparametric (Fornell, 1982). He went on to say that PLS's versatility and ability to shed light on intricate relationship models, as well as its ability to weed out irrelevant solutions and undetermined factors, made it an attractive option. In multiple regression, the problem of non-normal data is crucial. However, PLS-SEM can test hypotheses for their correlations among components and can deal with non-normal data (Hair et al., 2011).

3.13.5 Regression analysis

Regression analysis is used to investigate the links between a dependent variable and one or more independent variables, assisting researchers in identifying, forecasting, and evaluating the strength of these correlations. In basic linear regression, only one independent variable is used to predict the dependent variable, whereas multiple regression uses many predictors. A primary purpose of regression analysis is to assess whether there is a significant link between variables, which means that the observed relationships are unlikely to be random. This is usually measured using p-values and confidence intervals, which show the strength and reliability of the associations. In addition to examining individual associations, regression analysis takes into account model fit, or how well the regression model explains the variation in the dependent variable. Model fit is commonly measured using R-squared and adjusted R-squared values, which represent the amount of variance in the dependent variable explained by the model. A higher R-squared value indicates that the model better represents the data.

3.13.6 Mediation analysis

Mediation analysis is a statistical technique used to explore the process by which an independent variable (IV) affects a dependent variable (DV) through a third variable, known as the mediator. Essentially, it helps determine whether the influence of one variable on another occurs indirectly via an intermediary. This approach is especially valuable in fields such as social sciences, psychology, business, and behavioral research, as it allows researchers to delve into complex causal relationships and better understand the underlying mechanisms driving certain effects. In mediation analysis, researchers test the significance of the pathway from the IV to the mediator and from the mediator to the DV. The analysis reveals whether the mediator fully accounts for the IV-DV relationship (full mediation) or only partially explains it (partial mediation). In cases of full mediation, the IV no longer has a direct effect on the DV after including the mediator; with partial mediation, the IV still directly influences the DV alongside the mediator's indirect effect. Common techniques like bootstrapping or structural equation modeling (SEM) are often used to evaluate mediation effects. This approach enriches research findings by breaking down relationships into direct and indirect components, offering a more nuanced understanding of variable interactions. In order to examine the indirect effects of the relationships, the bootstrapping technique, as proposed by Preacher and Hayes (2008), was utilized to ensure accurate estimation of the confidence intervals (CIs) for the relationships.

3.14 Index creation

3.14.1 Stages in building composite index

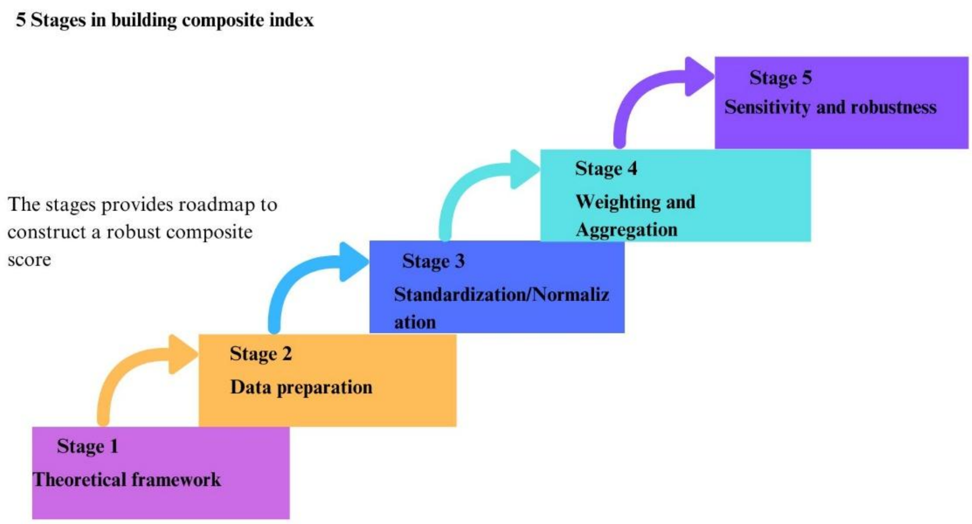


Figure 3.4 Composite index computation stages

There are five key stages in building a composite index (Figure 3.3).

3.14.1.1 Theoretical framework is required to support the study from the literature for the identification of the indicators.

3.14.1.2 Data preparation: Data preparation for index development includes essential procedures such as indicator selection, managing missing values, and performing multivariate data analysis. When selecting indicators, it is important to consider their relevance, accessibility, and theoretical frameworks to guarantee their appropriateness. Missing values, which have the potential to distort outcomes, should be resolved by imputation. Multivariate analyses facilitate the process of determining the appropriate weighting and aggregation, therefore offering a data-driven structure that augments the theoretical framework. Failure to follow these procedures can result in erroneous index creation and misinterpretation.

3.14.1.3 Standardization/Normalization: Indicators measured on multiple units and scales must be standardized, or normalized, for accurate aggregation. Resolving problems such as skewed data, outliers, and unequal scales, this stage guarantees comparability among indicators (Dobbie & Dail, 2013). Standardization aims to strike a compromise between reducing information loss and guaranteeing resilience. Given that various methodologies can affect the ultimate outcomes, it is advisable to do a sensitivity analysis and robustness testing to evaluate their effect on the composite index.

3.14.1.4 Weighting and Aggregation: A composite index is created by combining standardized indicators, where the weights assigned to each indicator indicate their relative significance (Figure 3.4). Distinct weighting approaches, such as statistical methodologies or expert judgment, might yield divergent outcomes. Equal weighting applies uniform treatment to all indicators; however, this approach may inadvertently assign greater importance to sub-indices that have a higher number of indicators. Data aggregation is commonly performed using either linear (additive) or geometric techniques (El Gibari et al., 2019). In contrast to geometric aggregation, linear aggregation is more compensatory and focuses on enhancing weaker indices. Non-compensatory approaches aim to achieve a balance among several objectives. It is advisable to use consistent weights for comparisons across time, although making adjustments may be necessary if priorities change.

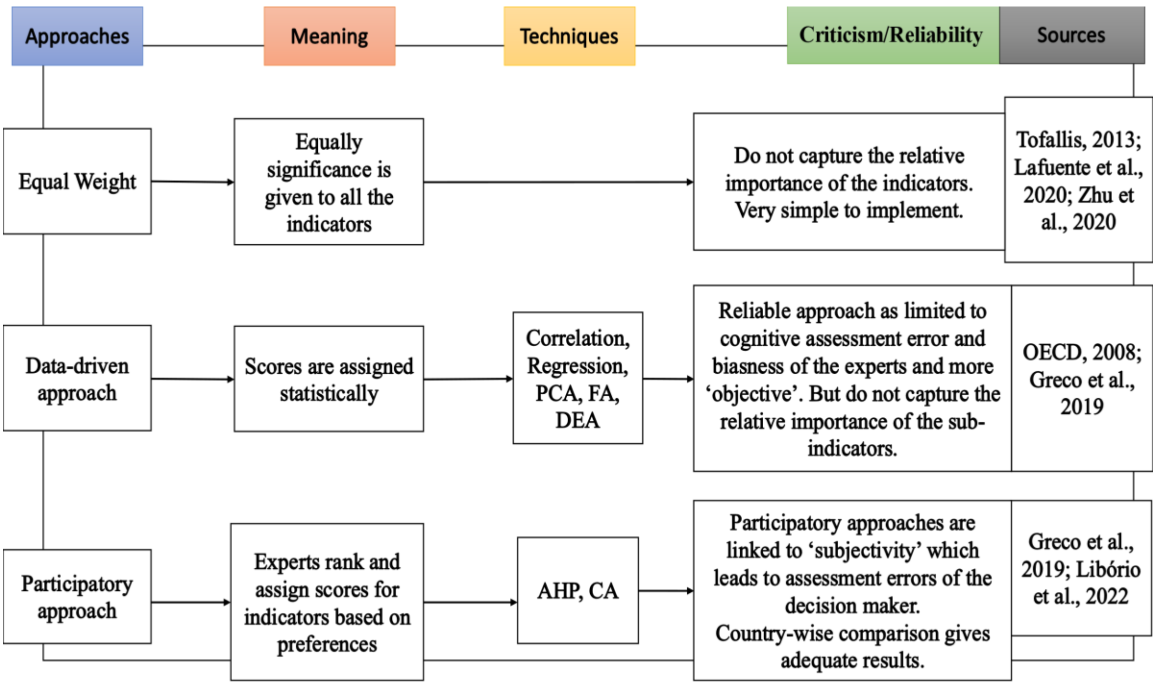


Figure 3.5 Summary of approaches for weighting sub-indicators

3.14.1.5 Sensitivity and robustness: The sensitivity and robustness of the composite index should be evaluated by subjecting important decisions, such as imputing missing values, normalization, and weighting, to sensitivity analysis throughout index construction

(Dobbie & Dail, 2013). Sensitivity analysis is a method used to evaluate the extent of variation and guarantee that the index accurately represents significant information related to the theoretical framework. Furthermore, it is important to measure the level of uncertainty in indicator scores in order to improve the reliability of the final index. Although robustness and uncertainty are generally addressed independently, including both approaches can enhance the index structure. However, only a limited number of studies comprehensively examine both elements.

3.14.2 Index formulation for this study

The computation of the composite index (CI) score was drawn on a methodology (Figure 3.5) using a data-driven weighted average approach. A comprehensive listing of all reviewed indices and their specific variables is too extensive for inclusion here. However, this table effectively highlights the contrasts between these established approaches and the methodology adopted in this study, allowing for direct comparison. Table 3.12 provides an in-depth illustration of the commonly used weighting approaches in index construction. Given the importance of reliable weighting (Figure 3.4), as discussed in literature review section, this study applies loading scores derived from factor analysis approach, using principal component analysis (PCA) as the extraction method along with varimax rotation to assign weights to each item (Nicoletti et al., 2000; Tresch et al., 2006). Notably, this study implements an FA approach by using squared factor loadings, as opposed to the traditional method that considers loading scores, enhancing the precision and reliability of the research model. To ensure a balanced impact of indicators, these weights are converted to absolute values.

Table 3.12 Summary of key differences and similarities of weighting methods

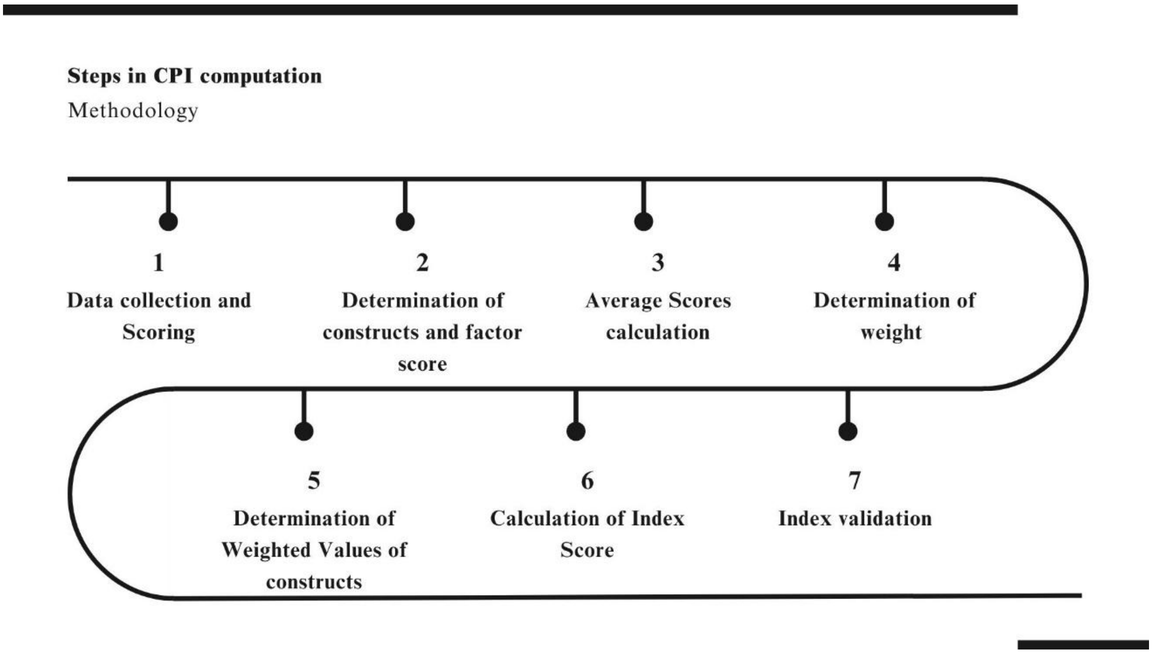
Basis	**EWM**	**PCA**	**FA**	**DEA**	**AHP**	**CA**
Weight	Equal for all	Variance-driven loadings	Common variance-based loadings	Efficiency optimization	Subjective pairwise comparison	Preferences
Flexibility	High	High	High, latent model-dependent	Flexible but requires an input-output structure	Flexible, relies on expert judgement	Flexible, adapts to preference data
Normalization	None	Standardization of components	Normalized by factor loadings	Input-output ratio adjustment	Pairwise comparison normalization	None
Aggregation	Simple average	Linear combination of indicators	Weighted sum by	Efficiency score aggregation	Pairwise comparison synthesis	Sum of the part worth utilities

			factor loadings			
Sensitivity	Low sensitive	Sensitive to variance	Sensitive to common variance	Sensitive to outliers	Sensitive to subjective judgements	Sensitive to preferences

Source: Author's own illustration

3.14.3 Steps in composite index score calculation

This study employs a multi-step methodology to calculate the final index score, which encapsulates overall performance across multiple service dimensions. The approach is systematically structured as follows:



Source: Author's own creation

Figure 3.6 Flowchart summarizing the methodology

Step 1: Data Collection and Scoring: To begin, scores were collected for multiple constructs, denoted as $\mathbf{C}_i$, where i represents different indicators of a construct. Each construct $\mathbf{C}_i$ yields a score S_{ij} that typically ranges from 1 to 7. A questionnaire was designed based on a comprehensive literature review, with respondents asked to rate each item on a 7-point interval scale (where higher scores indicate better performance).

Step 2: Determination of constructs and factor score: To identify the underlying constructs (C_i) in the dataset, FA was employed using PCA with varimax rotation in SPSS. PCA was chosen as it reduces dimensionality by identifying latent factors that explain the maximum variance in the observed variables while minimizing multicollinearity. Varimax rotation was applied to enhance the interpretability of the factor structure by producing factors that are uncorrelated and maximizing the loadings of each variable on one factor. The factor loadings (L_{C_i})represent the correlation between each latent construct (C_i) and the underlying observed items associated with each latent construct. These loadings quantify the contribution of each indicator to the overall factor.

***Step 3: Average Scores calculation**:* To quantify the overall performance of service providers across multiple constructs, we compute the average score for each indicator based on the performance scores. $\boldsymbol{S_{ij}}$ represents the performance score of the j^{th} CEP service providers in the i^{th} indicator for the construct C, $i \in \{1,2, 3, k\}$, $j \in \{1,2,3\ldots, m\}$. The average score reflects the cumulative performance across various items, ensuring that each construct is evaluated holistically. The average score (M_{C_i}) provides a single composite metric that summarizes the performance of service providers within a given construct.

Finally, the average score for each indicator within a construct (C_i) is calculated using Eq. (1).

$$M_{C_i} = \frac{1}{n}\sum_{j=1}^{k} S_{ij} \qquad \ldots (1)$$

Step 4: Determination of weight

a. *Weight indicator-wise:* To assess the contribution or weight of each item within a construct, the squared factor loading (λ_{c_i}) is calculated. Factor loadings are values that indicate how strongly each observed variable (item) is associated with a particular latent factor or construct. The λ_{c_i} for each indicator is calculated to assess the weight of each item Eq. (2):

$$\lambda_{c_i} = L_{C_i}^2 \qquad \ldots (2)$$

The squared factor loading λ_{c_i} shows how much of the variation in item i can be explained by the underlying construct C. Higher values of λ_{c_i} indicate that the item has a stronger relationship with the dimension, meaning it is a better representative of the latent construct.

Squaring the factor loadings provides a clearer understanding of the relative importance of each item within a dimension. It helps determine how well each item contributes to explaining the overall construct and can be used to evaluate the reliability or validity of the measurement model.

b. *Weight construct-wise:* To quantify the contribution of each factor within a construct, the total weights (ω_{C_i}) for each factor is determined by summing the individual weights (λ_{C_i}) of all its items associated with that construct. The total weights provide an aggregate measure of how well each construct is explained by its associated items. Constructs with higher total weights suggest a strong coherence between the observed items and the underlying factor, while lower total weights may indicate the need for model refinement. The (ω_{C_i}) for each indicator is calculated to assess the weight of each item in Eq. (3):

$$\omega_{C_i} = \sum_{i=1}^{k} \lambda_{C_i} \qquad \dots (3)$$

Step 5: Determination of Weighted Values of constructs

a. Weighted value per Item: To assess the contribution of each individual item within a construct, the weighted value (W_{C_i}) for each item was calculated. The weighted value combines the item's mean score with its weight, reflecting both its performance and its contribution to the underlying construct. This approach ensures that items with higher factor loadings, those more representative of the construct, are given appropriate weight in the analysis.
   Each Construct's weighted value (W_{C_i}) is calculated using Eq (4):

$$W_{C_i} = M_{C_i} x\ \lambda_{C_i} \qquad \dots (4)$$

b. Weighted value construct-wise: To quantify the contribution of each factor within a construct, the total weighted value (X_{c_i}) for each construct is computed by summing the individual weighted value of all items associated with that construct.

The formula in Eq. (5) is used to calculate the total weight of a construct C_i is calculated:

$$X_{c_i} = \sum_{i=1}^{k} W_{c_i} \qquad \dots (5)$$

Step 6: Calculation of Index Score: The final **index score** (IS_{c_i}) for each factor was computed by dividing the total weighted value (X_{c_i}) by the weight factor (ω_{C_i}) associated with that construct. This ratio normalizes the aggregate contribution of the items within the construct, providing a standardized index score that reflects the overall performance and relevance of the factor in the context of the model.

The formula for the index score of each construct is given by Eq. (6):

$$IS_C = \frac{X_{c_i}}{\omega_{C_i}} \qquad \dots (6)$$

Substituting the expression in Eq. (6), the index score can be expanded as Eq. (7):

$$IS_C = \frac{\sum_{i=1}^{k} W_{c_i}}{\sum_{i=1}^{k} \lambda_{c_i}} \qquad \dots (7)$$

Further, using the weighted value expression given in Eq. (4), the expanded formula to calculate the index score using Eq. (8):

$$IS_C = \frac{\sum_{i=1}^{k} M_{C_i} x \, \lambda_{C_i}}{\sum_{i=1}^{k} \lambda_{c_i}} \qquad \dots (8)$$

Incorporating the detailed formulation and using Eq. (1) and Eq. (2), the final expansion of the formula considering i^{th} item and j^{th} service providers is calculated using Eq. (9):

$$IS_C = \frac{\sum_{i=1}^{k} \left(\frac{1}{n} \sum_{j=1}^{n} S_{ij}\right) x \, {L_{C_i}}^2}{\sum_{i=1}^{k} {L_{C_i}}^2} \qquad \dots (9)$$

The construct C belongs to the set A, ($C \in A$), where A = {1,2,3…., n}. The final formula sums the weighted contributions of these constructs and normalizes them by the total weights of all the constructs as calculated by Eq. (10).

$$\boldsymbol{IS} = \frac{\sum_{C \in A} \left(\sum_{i=1}^{k} \left(\frac{1}{n} \sum_{j=1}^{n} S_{ij} \right) x \, L_{C_i}^2 \right)}{\sum_{C \in A} \left(\sum_{i=1}^{k} L_{C_i}^2 \right)} \qquad \ldots (10)$$

i, Indexes the individual items or dimensions within each construct. For each construct *C*, the items are indexed from *i*=1 to *k*, where *k* is the number of items in that construct.

j, Indexes the respondents or observations for the items. *j*=1, 2,…, n*,* where *n* is the total number of respondents.

k, Number of items within each construct. This varies depending on the construct.

n, Number of respondents or observations for each item.

Step 7: Index score validation*:* Confirming the accuracy of an index is essential in several domains like data analysis, finance, and research. The process guarantees the accuracy and reliability of the obtained outcomes, so enabling well-informed decision-making. In data analysis, index validation serves to authenticate the integrity of the data and the efficacy of the employed analytical methods. For example, financial evaluation is crucial for assessing the success of investment portfolios and making prudent investment choices. Index validation in research serves to demonstrate the credibility of the findings and conclusions derived from the analysis of the data. To check the validity, there is a requirement for the actual values derived from the data obtained from real-world observations.

3.14.4 Statistical metrics for index validation

There are various metrics that can be used to assess the quality of the predicted value. This study uses RMSE, MSE, MAE, and MAPE (Diep et al., 2024; Sabancı et al., 2023; Moreno et al., 2013*)* metrics to evaluate the reliability of the research model of the composite index.

a) ***Root Mean Square Error (RMSE)****:* The RMSE is a commonly employed metric to assess the level of accuracy of a model's predictions. The metric quantifies the average magnitude of prediction errors, emphasizing bigger errors resulting from the squaring of differences. It quantifies the square root of the average squared discrepancies between the anticipated Index Scores and the actual service performance level. The

RMSE serves as a measure of the precision of the Index Score, and is placed as Eq. (11).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{k}(Z_i - \hat{Z}_i)^2} \quad \dots (11)$$

Where, Z_i is the predicted value for the ith data point and $\hat{Z}_i$, is the actual value for the ith data point. A low RMSE value implies insufficient variance among the data points, therefore indicating a high degree of consistency and precision in the measurements. Conversely, a high RMSE value may indicate increased variability in the data, therefore adversely affecting the reliability and validity of the measuring instrument.

b) ***Mean Squared error (MSE):*** MSE is a commonly employed measure in regression analysis and machine learning to evaluate the accuracy of a model by computing the average squared variation between the actual and predicted values. It imposes a greater penalty on bigger mistakes, rendering it highly responsive to outliers and valuable for assessing the performance of a model. The non-negativity and differentiated characteristic of this quantity also contribute to its widespread use in optimization techniques. The formula is placed as Eq. (12).

$$MSE = \frac{1}{n}\sum_{i=1}^{k}(Y_v - \hat{Y}_v)^2 \quad \dots (12)$$

Where, Y_v is Predicted value**,** $\hat{Y}_v$ is Actual value

c) ***Mean absolute error (MAE):*** MAE is a statistical measure employed to assess the precision of a model by computing the mean of the absolute discrepancies between the observed and predicted values. It is less susceptible to outliers than MSE since it computes the absolute value of all mistakes equally. This is a clear and understandable metric that quantifies the performance of a model by providing the average size of prediction mistakes. The formula is placed as Eq. (13).

$$MAE = \frac{1}{n}\sum_{j=1}^{k}|Y_w - \hat{Y}_w| \quad \dots (13)$$

Where, Y_w is Predicted value, $\hat{Y}_w$ is Actual value. A higher MAE value signifies greater error relative to the variability in the dataset, reflecting lower accuracy. Conversely, a lower MAE indicates minimal deviation between predicted and actual values, implying better model performance.

d) ***Mean absolute percentage error (MAPE):*** MAPE is a popular metric to measure how accurate a forecast is. It figures out the average of the exact percentage differences between what happened and what was expected. This measure gives the error size as a percentage, which makes it simple to understand and compare across different results. The formula is placed as Eq. (14).

$$MAPE = \frac{1}{n}\sum_{j=1}^{k} \left| \frac{\hat{Y}_i - Y_i}{\hat{Y}_i} \right| x\ 100 \qquad \ldots (14)$$

Where, $\hat{Y}_i$ = Actual value, Y_i = Predicted value. A MAPE below 10% indicates a good level of accuracy, indicating that the model's predictions are in close proximity to the real values. A value within the range of 10% to 20% suggests favorable anticipated outcomes, which reflect reasonably strong predictions. Whereas, MAPE between 20% and 50% indicates satisfactory forecast outcomes, indicating competent performance of the model, but room for enhancement. Results above 50% indicate inadequate forecast accuracy, indicating that the model's predictions deviate significantly from the actual values and so cannot be relied upon.

3.15 Summary

This chapter presents the objectives and methodologies used in the study. These include research problem, research design, sampling techniques, research variables, data collection, data analysis tools and techniques, along with the need and scope of the study. This study is quantitative in nature and discusses sampling details for the objectives separately. The hypotheses used are also formulated objective-wise. Both the public and private CEP service providers operating under the geographical location of the study are included. Both individual and organizational customers meeting the criteria are considered for inclusion. A methodology is formulated to compute the Composite Index and used to measure CEP resilience. The computed index scores are evaluated through statistical metrics to assess the robustness through statistical validation. A conceptual framework of the courier service quality (CSQ) model is presented. Overall, this chapter outlines and justifies the methodology used to measure the CEP industry’s resilience against disruption and explores the level of competitive preparedness among the CEP service providers.