CHAPTER 5

RESEARCH METHODOLOGY

5 Research Methodology

This chapter presents the development of the research design and provides a rationale for the selection of research methods used in this study. Before this, the literature review has described the research trends and adoption models in studying IoT adoption and acceptance. Following the literature review, previous chapters have discussed the research framework and hypotheses development.

This chapter is organized as follows: Following the introduction, the next section discusses the underlying philosophical point of view and approach considering the paradigms in supply chain research. Subsequent section discusses the research design and stages, whereas the last section describes the process to build a logistic regression model.

5.1 Research Paradigm

(Earl-Babbie, 2013) describes a research paradigm as essential models or frameworks that shape our observation and reasoning processes. This paradigm lies at the heart of research design, varying based on individual perspectives, and encompasses multiple viewpoints or paradigms. Similarly, (Kuhn, 2012) characterizes a research paradigm as a worldview, encompassing *“people's value judgments, norms, standards, frames of reference, perspectives, ideologies, myths, theories, and accepted procedures that guide their thoughts and actions”*. (Bryman et al., 1988) further elaborates on this concept, explaining that a paradigm is a set of beliefs and directives that influences scientists within a specific discipline in terms of what to study, how to conduct research, and the interpretation of results.

This framework is crucial for understanding and explaining social phenomena, nature, and beliefs. Before delving into specific aspects, it's imperative to grasp the underlying research philosophy, which provides insight into phenomena and directs the research process. Researchers must consider three fundamental philosophical orientations: epistemology, ontology, and axiology.

Epistemology, as explained by (Bryman, 2016) in his work, deals with the understanding and systems of knowledge. It focuses on the perspective of the researcher, particularly what they deem as credible or acceptable knowledge. This aspect is centred on the researcher's approach to viewing the world, whether they are objective and base their understanding solely on personal experiences. The concept of epistemology is typically divided into two main schools of thought: positivism and interpretivism.

Ontology, as described by Saunders (Saunders et al., 2003)publication, is the study of the essence of reality, which is often explored through the testing of theories related to objects or structures. This field of study is divided into two key perspectives: objectivism and subjectivism. Objectivism posits that social entities exist independently of people's awareness or perception of them. A researcher with a positivist orientation is likely to adopt an objective stance towards reality. On the other hand, subjectivism suggests that social phenomena are shaped by individuals' observations and actions. Researchers who lean towards interpretivism typically view reality as subjective and socially constructed. As a result, different individuals may perceive the same situation in varied ways, influenced by their personal worldview. These varied perceptions can significantly impact researchers' decisions, their interactions, and the nature of their social engagement with others.

Axiology, as Saunders (Saunders et al., 2003) explain, is the philosophical study that focuses on value judgments. It reflects how a researcher's values influence their choice of philosophical approach, and it also examines the impact of these values on the methodologies and data collection techniques used in research. Researchers who adopt a positivist perspective maintain objectivity and detachment from the data and subjects they study, ensuring that their research activities do not influence the outcomes. In contrast, as Collis and Hussey (Collis & Hussey, 2014) point out, interpretivists believe that their personal knowledge and values play a crucial role in shaping what is considered as factual, and the interpretations derived from these facts. Interpretivists aim to gain deeper insights into specific contexts. Therefore, they often employ exploratory methods such as case studies, interviews, focus groups, and ethnography, which are seen as more appropriate for gaining a comprehensive understanding of the subject matter.

The influence of research paradigms on research design is significant. In the context of positivism, there's a prevailing view that humans should be studied as part of the natural-scientific world, emphasizing objectivity. When adopting an objectivist approach in research, methods like surveys and questionnaires are commonly used for their objective nature. These tools are effective in quantifying data in a structured manner. Conversely, the interpretivism paradigm, which stands in contrast to positivism and is sometimes referred to as anti-positivism, suggests a different approach to social science. This perspective emphasizes the importance of subjectivity in social sciences. As a result, researchers who align with interpretivism often employ exploratory techniques like focus groups, case studies, in-depth interviews, and observation. These methods are chosen for their ability to provide a more subjective understanding of the world, as noted by Saunder.

This study adopts a scientific methodology grounded in the positivism approach. From an ontological standpoint, it embraces an objective viewpoint aligned with positivism, implying that the research remains unaffected by the subjects being studied. Given that the primary goal of science is to address issues and answer questions from a social scientific perspective, objective methods were employed to ensure reliable empirical findings.

5.2 Research Design and stages.

"Research design is what you are going to observe and analyze: why and how" (Earl-Babbie, 2013). So, to conduct research, one has to decide what to find out and the best way to do it. Research design describes the process to go about designing a study and also create a roadmap to conduct research. Research design in this section divided into three stages:

1) conceptualization, operationalization of constructs, and questionnaire development,
2) sampling design, and
3) modes of observation.

Table 11 Empirical study variables

Purpose of the study	**Hypothesis testing**
Types of investigation	Correlation, predictive relationships
Extent of researcher's interference Study setting	Minimal
Study setting	Field study
Unit of analysis	Organisational level
Sampling design	non probabilstic,purposive and judgemental n=150
Time horizon	One shot, cross-sectional study
Data collection method Measurement of variable	Google form sent on email and pursued on telephone
Measurement of variable	Element definition, interval scale (seven point Likert scale), nominal, and dichotomous scales

5.2.1 Conceptualization, Operationalization and Questionnaire Development

5.2.1.1 Conceptualization

Social science research starts with exploring the topic to gain understanding. In this research, an extensive literature review has been performed to examine the adoption of IoT in manufacturing.. The literature review also includes all relevant existing studies describing models, methods and the relationship of different IoT adoption model constructs, i.e., Technology, Organization and Environment constructs. From the literature review and real-world observation (through semi-structured interview of experts) research gap has been identified, and to fulfil the same, the conceptual framework has been developed for studying the impact of technology, Organization and environment on IoT adoption in textile manufacturing at an organization level(Tornatzky et al., 1990).

All constructs of the study, i.e., constructs in the Technology, Organization and Environment, contexts have been conceptualized after a thorough literature review. For example, deep analysis of the study and models proposed by (Rogers et al., 1983). (Tornatzky et al., 1990), (Iacovou et al., 1995b) have been amalgamated to build the conceptual network. Constructs of perceived direct benefits, perceived indirect benefits, perceived financial costs(Kuan & Chau, 2001), compatibility, firm size, trading partner pressure and information intensity(Y. M. Wang et al., 2010) have been built in into the conceptual framework.

In the conceptual framework outlined, the TOE (Technology, Organization, Environment) framework is comprised of three key components. Wang(Y. M. Wang et al., 2010) identified these components as playing a dual role; they serve as both barriers and catalysts for technological advancements. This dual nature affects how companies perceive the necessity for, seek out, and integrate new innovations. Within the context of this research, the adoption of IoT is described as the process of assimilating this technology(Grover, 1993). This observation is in harmony with the initiative to examine the IoT adoption trends arising from Indian textile organizations and their influence on the interactions among the elements of the conceptual framework. With this perspective, the TOE framework is positioned as the fundamental theory. Concurrently, innovation diffusion theory plays a supporting role, primarily addressing the origins of stakeholder pressure. This pressure represents just a single aspect of the various factors influencing IoT adoption. Based on consolidation stages and assimilation contexts discussed above, we developed a conceptual model as shown in the previous chapter. Drawing upon our earlier discussion, IoT adoption is the dependent variable. The model also incorporates the technological, organizational, and environmental contexts as predictor variables. As explained earlier, the specific factors within each context were obtained from review of literature(Zhu & Kraemer, 2005)

5.2.1.2 Operationalization

As discussed above, very little research has been conducted in the context of textile manufacturing IoT adoption and most of them have used a review approach. Therefore, to operationalize the constructs in the model, direct use of instruments in previous studies is not always possible.(Kuan & Chau, 2001) Over half of the items used were therefore specially developed for this study based on the literature review of sources, including trade journals and pamphlets published by suppliers of IoT.

Perceived direct and indirect benefits were operationalized by items taken from Iacovou (Iacovou et al., 1995b). Perceived financial costs were measured by three items based on either prior studies(Arunachalam, 1995),(Drury & Farhoomand, 1996). Items for the compatibility, firm size, and information intensity were adapted from Grover (Grover, 1993) . The measures trading partner pressure were adapted from Iacovou (Iacovou et al., 1995b),Internationalization readiness was adapted from the seminal paper of Thi (Thi Ha Uyen Tran, 2020) and regulatory support from Zhu (Zhu & Kraemer, 2005). The binary dependent variable, adoption, measured whether a company had adopted or not adopted IoT (0: non- adopter, 1: adopter). The construct was operationalized via a yes/no response to the question “Has my company adopted an IoT in manufacturing?”(Y. M. Wang et al., 2010). For the predictor variable a 7 point Likert scale was used with anchors of “Strongly Disagree” to “Strongly agree” as used in the original reviewed literature.

Table 12 Items and their sources

Constructs	Source	Code	Item
Perceived direct benefits	(Iacovou et al., 1995b)	PDB1	IoT adoption in my firm will improve data accuracy
		PDB2	IoT adoption in my firm will improve security of data
		PDB3	IoT adoption in my firm will improve operational efficiency
		PDB4	IoT adoption in my firm will speed up the order status updation process
Perceived Indirect benefits	(Iacovou et al., 1995b)	PIB1	IoT adoption in my firm will reduce clerical errors
		PIB2	IoT adoption in my firm will improve organization image
		PIB3	IoT adoption in my firm will improve competitive advantage
		PIB4	IoT adoption in my firm will benefit other business practices of my company

Constructs	Source	Code	Item
		PIB5	IoT adoption in my firm will improve customer services
		PIB6	IoT adoption in my firm will improve relationship with business partners
Compatibility	(Grover, 1993)	CP1	The changes introduced by IoT adoption is consistent with my company's beliefs/values
		CP2	IoT is compatible with my firm's current information infrastructure
		CP3	My company believes that IoT adoption is compatible with it
Firm size	(Grover, 1993)	FS1	The capital of my company is high compared to industry
		FS2	The revenue of my company is high compared to industry
		FS3	The number of employees in my company is high compared to the industry
Perceived financial cost	(Drury & Farhoomand, 1996)	PFC1	IoT adoption has high set-up costs in textiles
		PFC2	IoT adoption has high running costs in textiles
		PFC3	IoT adoption has high training costs in textiles
Internationalization readiness	(Thi Ha Uyen Tran, 2020)	IR1	My company has unique and differentiated products that meet expectations of international customers
		IR2	My company has adequate financial resources and qualified

Constructs	Source	Code	Item
			export personnel and experience for export activities
		IR3	My company' top management is committed heavily towards international business
Trading partner pressure	(Iacovou et al., 1995b)	TPP1	The major trading partners of my company encourage use of IoT
		TPP2	The major trading partners of my company recommend implementation of IoT
Information Intensity	(Grover, 1993)	IT1	The product in my industry requires a lot of information to sell
		IT2	The product in my industry is complex to understand or use
		IT3	The ordering of products in my industry is a complex process
Regulatory support	(Zhu & Kraemer, 2005)	RS1	The government is providing incentive for adoption of IoT technologies
		RS2	Business laws support Internet based textile business

5.2.1.3 Questionnaire development

Many methods are used to achieve broad coverage of various dimensions of constructs discussed in the previous section. A semi-structured interview was conducted for conceptualizing construct and understand its relevance in practice with the experts. The established scale was used to measure the different variables used in the study. Further, these scales were pilot-tested to determine its' usability in the Indian context.

Measurement scales for PDB,PIB were taken from Iacovou(Iacovou et al., 1995b)and PFC were taken from Arunachalam and Drury((Arunachalam, 1995),(Drury &

Farhoomand, 1996), compatibility, firm size were taken from Grover(Grover, 1993), as also information intensity. Trading partner pressure from Iacovou and regulatory support from Zhu(Zhu & Kraemer, 2005). (Refer Appendix 12 for the questionnaire)

5.2.2 Preliminary assessment of questionnaire

5.2.2.1 Content Validity

Content validity is defined as “the degree to which items in an instrument reflect the content.

universe to which the instrument will be generalized” (Straub et al., 2004).

A panel of 15 industrial experts were administered the questionnaire and asked to rate the items from 3= essential to 1= not essential.

The Lawshe’s method was used with the expert panel to rate the content and calculate the CVR (content validity ratio)(Taherdoost, 2018). Depending upon the number of panelists, the cut-off value for .the CVR is given below (Taherdoost, 2018)

Table 13 CVR Cut off values.

MINIMUM VALUE OF CVR, P = .05, SOURCE: (LAWSHE, 1975)

No. of Panellists	Minimum Value
5	.99
6	.99
7	.99
8	.75
9	.78
10	.62
11	.59
12	.56
13	.54
14	.51
15	.49
20	.42
25	.37
30	.33
35	.31
40	.29

Based on the ratings from the expert panel, the scores for each of the items were arrived at as below Table 14.

Table 14 Item wise CVR

Code	**Number of experts(N)**	**(Ranked as essential)N_e**	**CVR (content validity ratio)**
PDB1	15	13	0.73
PDB2	15	13	0.73
PDB3	15	13	0.73
PDB4	15	13	0.73
PIB1	15	12	0.60
PIB2	15	12	0.60
PIB3	15	13	0.73
PIB4	15	12	0.60
PIB5	15	13	0.73
PIB6	15	12	0.60
CX1	15	13	0.73
CX2	15	13	0.73
CP1	15	12	0.60
CP2	15	13	0.73
FS1	15	12	0.60
FS2	15	13	0.73
FS3	15	12	0.60
PFC1	15	12	0.60
PFC2	15	12	0.60
PFC3	15	12	0.60
IR1	15	12	0.60
IR2	15	13	0.73
IR3	15	12	0.60
TPP1	15	13	0.73
TPP2	15	13	0.73
TPP3	15	12	0.60
IT1	15	13	0.73
IT2	15	12	0.60
IT3	15	13	0.73
RS1	15	13	0.73
RS2	15	12	0.60

All items were meeting the requirements of the cut-off value for content validity. Content validity is essentially to ensure that the items are valid in the Indian context. The experts were CEOs and heads of supply chain for some of the established and the upcoming textile manufacturing units in the country. Care was taken to address all the segments as will be visible from the final data collection.

5.2.2.2 Reliability of items

Based on the content validity results, a pilot study of 52 responses was collected and analysed for Cronbach's Alpha(F. Hair Jr et al., 2014). The results are given in the Table 15.

Table 15 Item wise Cronbach alpha values

Code	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha
PDB1	147.5723684	548.197	.613	.927
PDB2	147.5723684	548.197	.613	.927
PDB3	147.6052632	552.089	.439	.929
PDB4	147.6052632	552.089	.439	.929
PIB1	146.9210526	567.379	.479	.929
PIB2	146.8684211	561.655	.565	.928
PIB3	147.0263158	563.381	.503	.929
PIB4	147.0263158	563.381	.503	.929
PIB5	146.8684211	561.655	.565	.928
PIB6	147.0263158	563.381	.503	.929
CP1	147.8026316	547.428	.583	.928
CP2	147.7105263	550.816	.551	.928
CP3	147.9539474	560.016	.364	.930
FS1	147.3947368	557.967	.729	.927
FS2	148.0263158	535.952	.711	.926
FS3	148.0789474	546.722	.568	.928
PFC1	148.1842105	553.847	.431	.929
PFC2	148.1315789	553.924	.433	.929
PFC3	148.3421053	567.324	.230	.932

Code	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha
IR1	148.9210526	573.796	.385	.930
IR2	148.9210526	573.796	.385	.930
IR3	148.9671053	572.814	.386	.930
TPP1	147.7105263	547.679	.531	.928
TPP2	147.9210526	543.613	.528	.928
TPP3	148.0789474	541.891	.524	.928
IT1	147.6052632	548.867	.520	.928
IT2	147.8947368	546.299	.534	.928
IT3	148.1842105	548.627	.437	.930
RS1	148.7105263	548.549	.517	.928
RS2	148.0789474	535.876	.651	.927

As we notice all Cronbach Alpha values are 0.9 and above thus indicating reliability of the items.

With the questionnaire being put through the validity and reliability test, it was found satisfactory to use the questionnaire for data collection

5.3 Sampling design

Current research in the supply chain and technology area were studied in the context of western countries, which has different economic and social scenarios than developing economies such as India. Globalization has also taken manufacturing to emerging economies like India. India, amongst the South-Asian countries, arises as an important player contributing significantly to the manufacturing industry and thus playing an essential role in the global supply chain. Therefore, the study of IoT and its adoption become imperative. However, due to a significant portion of "Indian manufacturing units are unorganized and unregistered across the country," create challenges in sampling for business research (R. Singh & Mangat, 2013).

India, with its vast geographical expanse, presents significant challenges in collecting representative samples from various regions. To address this, our study employed two strategies. Initially, we focused on Ahmedabad and its nearby areas, known as the nation's textile heartland, to mitigate data collection imbalances and ensure adequate representation from different sectors. Later, we administered the questionnaire to professionals in textile units pan India based on the TEXPROCIL database Additionally, we prioritized gathering data from reliable sources rather than depending solely on lesser-known ones. This approach is particularly vital for business research in India, especially when targeting a specific demographic, which is inherently complex. (Pandey et al., 2010) best summarize the issue: “The Indian experience of mailed surveys using the random sample from an industrial database has not been encouraging.” Moreover, (Hoskisson et al., 2000) “strongly encouraged and suggested the use of credible local sources when collecting data in developing countries such as India and China.” (Cai, 2013) cited “an explicit effort to collaborate with local investigation firm to conduct the study, in an endeavour to obtain reliable information relating to emerging economies.”

5.3.1 Sampling Frame

The TEXPROCIL (textile promotion council of India) is the organization which is helping textile firms that have technologically upgraded or are in the process of upgrading production processes. Registration in TEXPROCIL is mandatory for applying for TUF (textile upgradation fund). Therefore, this is the most comprehensive database of textile firms in India. This database has 2000 registered manufacturing firms and 1000 textile trading firms. India being a vast country presents challenges in sampling (Willis et al., 2016).Therefore in B2B research at an organization level we focused on 200 firms (A. S. Singh & Masuku, 2013).

5.3.2 Sampling method

Given the geographical challenges and the fragmented industry structure, we start with non-probabilistic convenience sampling and build into judgemental sampling. The survey targeted the IT personnel at mid management level in the said firms. The questionnaire was administered as a google form to the target audience. The companies were chosen with the help of industry experts (A. S. Singh & Masuku, 2013) representing each segment in TEXPROCIL.

Table 16 Sample frame segments

Segment	Percentage
Apparel & fashion	24%
Apparel & Fashion, import & export, textiles	3%
Apparel & Fashion, internet, manufacturing	3%
Apparel & Fashion, manufacturing	3%
Apparel & Fashion, Online shopping, manufacturing	2%
Apparel & Fashion, retail, manufacturing	22%
Apparel & Fashion, retail, textiles, manufacturing	1%
Apparel & Fashion, textiles	1%
Apparel & Fashion, import & export, textiles	1%
Mechanical or Industrial engineering textiles	2%
Furniture textiles	1%
Textiles	1%
Textiles manufacturing	36%

Source: TEXPROCIL

In order to reduce bias in the sample, care was taken to choose equal number of adopters and non-adopters. The questionnaire was administered after asking the first question “has our firm adopted IoT in manufacturing?”

5.3.3 Sample size.

In research that relies on survey methods, selecting an appropriate number of participants is essential for ensuring that the study's results can be applied to the broader population accurately, with a specific level of accuracy and trust.(Hair Jr et al., 2019), (Sekaran & Bougie, 2016). The ability to generalize findings is influenced by several factors, including the goals of the research, the chosen confidence interval and level, population size, and the statistical methods employed(Fowler Jr, 2013);(Hair Jr et al., 2019); (Sekaran & Bougie, 2016)). In studies that utilize logistic regression, it is typically necessary to choose a large sample size. This helps in analyzing the predictive relationships between variables and ensures the reliability of the estimates and the statistical power of the study(Kline, 2017); (Tabachnick & Fidell, 2014)). Therefore, defining an appropriate minimum number of participants for logistic regression is crucial (Gerbing & Anderson, 1988);(Kline, 2017).

Regarding the minimum number of participants for logistic regression applications, there's no universally agreed-upon number (Gerbing & Anderson, 1988),(Hair Jr et al., 2019),(Kline, 2017). Anderson and Gerbing proposed a minimum of over 150 participants, whereas Kline (suggested that at least 200 participants are generally considered sufficient. According to Kline , the complexity of the model should guide the decision on sample size. Specifically, a model with more variables, requires a larger sample. A common heuristic is the cases-to-variables ratio, often recommended to be between 5 and 7 (Hair Jr et al., 2019). We have 30 questions in the questionnaire and therefore our sample size is 150.

5.4 Unit of Analysis

This study is initiated with an in-depth review of IoT and its relevance in practice. Integrative behaviors of the manufacturer will lead to increased adoption for improving performance. Thus, this study requires a response from the individuals who worked in the supply chain or operations domain, having a thorough understanding of the supply chain and cost to adopt IoT. Therefore, individuals working as the capacity of supply chain executives, managers, procurement manager, finance manager, VP (supply chain), etc. were included for data collection.

5.5 Modes of Observation and Selection of Research Method

5.5.1 Quantitative Method

This research aims to study the relationship between Technological, Organizational and environmental constructs. As mentioned, Technology has been categorized into three dimensions 1) perceived direct benefits, 2) perceived indirect benefits, and 3) compatibility. Organizational construct was also proposed to study across three dimensions, i.e., 1) Firm size,2) Perceived financial costs 3)International readiness. The environment construct is described by 1) Trading partner pressure 2) Information intensity 3)Regulatory support. The conceptual framework has been developed to explore the relationship between the constructs and hypotheses has been established previously. Since this study is descriptive and describing the adoption constructs and its impact, the survey method is the best quantitative method suits to conduct this study.

5.5.2 Large Scale Survey - Main study

The data collection or large-scale survey is the final and essential component of the research design process. The final survey for the main study was carried out between August 2023 and December 2023 pan India. Since the manufacturing sector in India is highly unorganized, and emails followed up with phone calls were used to collect data . Data were collected from the working professionals. The judgemental sampling method was also employed to increase the participation of working professionals in the data collection process. With these techniques, around 300 representatives from different companies were contacted data collection.

We also used LinkedIn to send questionnaires to industry professionals and some of them responded. In total, finally 176 responses were received. Out of these 24 had to be rejected due to incomplete filling of the google sheets and hence the final data set was 152 respondents.

5.5.3 Analytical procedure

This research is primarily based on the conceptual framework developed from the theoretical model as explained earlier. SPSS was the software used to run the Principal Component analysis and the forward logistic regression

5.6 Logistic regression

Logistic Regression is identified as a statistical approach that applies the logistic function to model outcomes that are dichotomous in nature, essentially focusing on binary outcomes such as success or failure, yes or no decisions. This methodology calculates the likelihood of a binary outcome based on a combination of independent variables and their corresponding regression coefficients, represented mathematically as: X=[X0, X1, X2, X3...Xn]^T. Predictor Variables B=[β0, β1, β2, ... βn]^T – Regression Coefficients P=probability β0- Intercept To ensure the output probability lies within the range of 0 to 1, the logistic function outcome is normalized by its addition to 1. $\ln(p/(1+p)) = \beta 0 + X1\beta 1 + X2\beta 2 + ... + Xn\beta n$. Utilizing SPSS software for statistical analysis allows for detailed examination of selected outcomes, incorporating procedures for displaying each phase in the model's optimization, including classification plots, the Hosmer-Lemeshow test for goodness of fit, variable correlation analysis, iteration history, and model constants. The default settings include a classification threshold of 0.5, a maximum of 20 iterations, with criteria for step-wise entry and removal set at 0.05 and 0.10, respectively. The forward method incrementally builds the model, adding variables that significantly contribute and removing non-significant variables.