Chapter 5: Mixed methods research - why and how to use it

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Summary
This chapter elucidates and justifies mixed methodological foundations and research design. It describes mixed-method research design with justification of the choice of methodologies. This chapter can be used by postgraduate researchers who are considering following this approach or applying it. The case study of consumers' perceptions towards HSBC visual identity is employed to illustrate how mixed-method approach can deliver insight.

Justifying the research methodology

The importance of a paradigm

According to various researchers (e.g. Burrell and Morgan 1979; Deshpande 1983), the marketing paradigm is significant. IN academic marketing research, the researcher defines a set of underlying assumptions that serve as a guideline to understand the subject as well as generate valid and reliable results. A paradigm is a cluster of beliefs which, for scientists in a discipline, influence what should be researched, how study should be done and how the results should be interpreted (Bryman 2004). Tashakkori and Teddlie (1998) indicate that paradigms are opposing worldviews or belief systems that are an indication of and guide the decisions that researchers make.

Paradigms are systems of interrelated ontological, epistemological and methodological assumptions. Ontological is how the researcher regards the nature and form of social reality. Epistemology is the assumption of how people know things and the association between the researcher and the phenomenon studied (nature, sources and limits of knowledge). The methodology paradigm is the technique used by the researcher to discover reality - it relates to the questions and techniques used in a study to collect and validate empirical evidence (the process of conducting the inquiry) (Creswell 2003, Foroudi *et al.* 2014). According to Lincoln and Guba (2000), these claims can be called 'paradigms' or can be considered as research methodologies.

Positivism and interpretivism

In social research, two dominant epistemological assumptions are interpretivism-idealism-phenomenology and positivism (e.g. Cassell and Symon 1994, Corbetta 2003, Deshpande 1983; Easterby-Smith *et al.* 2002). Previous studies employed the terms "naturalistic" and "scientific", whereas Tashakkori and Teddlie (1998) use the terms "positivist" and "constructivist". The main classification of each philosophical assumption is presented in Table 5.1.

Interpretivism is social research that aims to develop an understanding of social life and discover how people construct meaning in natural settings (Neuman 2003). Interpretivism addresses the process of interaction between individuals while taking account of the fact that their background shapes their construction of meaning, and pragmatism, which deals with actions, situations and consequences rather than antecedent conditions (Creswell 2003). Phenomenology views the world as the qualitative paradigm (Deshpande 1983). The interpretivist approach is concerned with building inductive hypotheses, studying phenomena through direct experience in order to understand the world (Bryman 2004).

Positivism is the oldest and most widely used approach; it is broadly a natural sciences approach. Positivist approaches aim to improve understanding by adopting different methods. Positivism uses the scientific deductive method to conduct empirical and quantitative research (Creswell 2003). The logical positivist view of the world is synonymous with the quantitative paradigm (Deshpande 1983). Furthermore, positivist research employs procedures associated with inferential statistics, hypotheses testing, and experimental and quasi-experimental design. Positivism assumes that social reality is external and should be measured by objective methods (Creswell 2003).

	Positivist paradigm	**Phenomenological paradigm**
Basic beliefs	The world is external and objective	The world is socially constructed and subjective
	Observer is independent	Observer is part of what is observed
	Science is value-free	Science is driven by human interests
Preferred methods	Focus on facts	Focus on meanings
	Look for causality and fundamental laws	Try to understand what is happening
	Reduce phenomenon to simplest elements	Look at the totality of each situation
	Formulate hypotheses and then test them	Develop ideas through induction from data
	Taking large samples	Small samples investigated in depth or over time

Table 5.1: Research paradigms
Source: Easterby-Smith *et al.* (2002); Foroudi (2012)

To choose which paradigm would lead to a more accurate investigation, the nature of research questions and objectives should be considered. Deshpande (1983) recommends that marketers focus on both paradigms: the positivism and the idealism paradigm (theory verification and theory generation) to avoid method-bias, which frequently occurs due to focusing on one paradigm. Paradigms should not be considered mutually exclusive (ways of describing these paradigms are illustrated in Table 5.2). The theory generation allows the researcher to develop propositions to be tested later, perhaps using theory verification by quantitative methods.

Positivist	**Interpretive**
Quantitative	Qualitative
Objectivist	Subjectivist
Scientific	Humanistic
Experimentalist	Phenomenological
Traditionalist	Revolutionist

Table 5.2: Alternative paradigm names
Source: Foroudi (2012); Malhotra and Birks (2000, p. 138)

Pursuing both paradigms has two main results (Table 5.3). The use of qualitative study to obtain preliminary insights into study problems can establish an appropriate scale to measure the focal construct of the research, which can be used later to test theories and hypotheses. It also it helps to identify a new set of scales, which may be useful in measuring marketing constructs. Second, it improves the validity, reliability and generalisability of the research (Bryman 2006; Creswell 2003) by employing a positivist paradigm to test the model, hypotheses and their causal relationship (Shiu *et al.* 2009).

	Quantitative Research	**Qualitative Research**

Purpose	Deductive: verification and outcome oriented, precise measurement and comparison of variables, establishing relationships between variables, interface from sample to population	Inductive: discovery and process oriented, meaning, context, process Discovering unanticipated events, influences and conditions, inductive development of theory
Research questions	Variance questions, truth of proposition, presence or absence, degree or amount, correlation, hypothesis testing, causality (factual)	Process questions, how and why, meaning, context (holistic), hypotheses as part of conceptual framework, causality (physical)
RESEARCH METHODS		
Relationship	Objectivity/ reduction of influence (research as an extraneous variable)	Use of influence as a tool for understanding (research as part of process)
Sampling	Probability sampling, establishing valid comparisons	Purposeful sampling
Data collection	Measures tend to be objective, prior development of instruments, standardisation, measurement/testing-quantitative/categorical	Measures tend to be subjective, inductive development of strategies, adapting to particular situation, collection of textual or visual material
Data analysis	Numerical descriptive analysis (statistics, correlation), estimation of population variables, statistical hypothesis testing, conversion of textual data into numbers or categories	Textual analysis (memos, coding, connecting), grounded theory, narrative approaches
Reliability/Validity	Reliable, technology as instrument (the evaluator is removed from the data)	Valid, self as instrument (the evaluator is close to the data)
Generalisability	Generalisable, the outsider's perspective, population oriented	Ungeneralisable, the insider's perspective

Table 5.3: Comparison between qualitative and quantitative approach
Source: Foroudi (2012), Maxwell and Loomis (2003, p. 190), Steckler*et al.* (1992).

The central research question and the research model
Before deciding on the specific research method, the researcher should determine what type of relationship is under investigation. For example, it is increasingly common for academic marketing researchers to use structured equation modelling, because it is an ideal tool for disentangling the relationship between complex sets of variables. For example, if the researcher wants to find, in a given sample, the relative importance of consumers perceptions of the quality of customer service in banking, their perceptions of bank brands, whether they use several banks, and their loyalty to their main banks, then structured equation modelling would be appropriate to find the relative importance of these variables and whether one or more variables mediated the relationship between a given variable and the object of the study, loyalty to their main bank. However, if the object of the study is to find out for which customers the relationship between perceptions of customer service and loyalty was strong and for which it was weak, then more classic statistical methods might be better.

There is no right answer, but it can be argued than one determinant of the approach should be whether the research study aims to provide practical helps to management. In the above case, for example, it could be argued that management are well aware of the importance of the variables mentioned – they are all important. So, management does not need another study exploring in detail the relationship between variables but would find a study which contributes to segmenting between different types of customers very helpful. Too often, academic researchers decide that they want to study a topic without regard for management implications, and then have to force some conclusions about management implications based upon the analysis method or the model that they decided to use. This approach is bound to lead to reduced relevance in their work.

Selection of research approach

To provide a more comprehensive approach to increasing the understanding of the research problem, the best fit was the pluralism research approach (Deshpande 1983, Mingers 2001). Mingers (2001) states, "the different research methods (especially from different paradigms) focus on different aspects of reality and therefore a richer understanding of a research together in a single piece of research or research program……combining several methods" (p. 241). Deshpande (1983) and Mingers (2001) believe that ignoring the potential contribution of methods related to non-positivist approaches (e.g. in-depth interviews) probably limits the understanding of researchers who use the positivist approach.

The use of more than one research method (focus group, interview, and questionnaire) enriches the understanding of the phenomenon under study and can reveal new insights (Creswell 2003, Foroudi *et al.* 2014). Based on the development of research methodology and perceived legitimacy of both quantitative and qualitative research, social and human sciences researchers increasingly use the mixed-methods approach (Foroudi *et al.* 2014). Creswell (2003) states that the approach is a "quantitative study based on testing a theory in an experiment with a small qualitative interview component in the data collection phase" (p. 177). Qualitative and quantitative approaches may be collected sequentially to confirm, cross-validate, or corroborate findings at one stage in the research process.

The phases of research

Four phases can be identified

- Initiation, before the data collection e.g. when the study problem/measures/sample are created;
- Implementation - the sequence the researcher uses to collect both quantitative and qualitative data (Creswell *et al.* 2003);
- Integration - occur within research questions, data collection, data analysis (Creswell *et al.* 2003);
- Interpretation, when conclusions are drawn to strengthen the knowledge claims of the research or must give explanation any lack of convergence that may result.

The mixed method approach used to be used mainly in the data collection phase., but now it is used at different stages of the research - problem setting, theory building, and data collection, analysis and interpretation (Bryman 2006, Creswell 2003). The mixed methods approach increases a construct's reliability and validity (e.g. Bryman 2006, Churchill 1979, Creswell 2003). Also, combining qualitative and quantitative methods often enhances their strengths (Foroudi *et al.* 2014).

Analysing qualitative data

The analysis of qualitative data can be carried out by content analysis. Bryman (2006) identified two schemes to justify the combination of quantitative and qualitative research based on a content analysis. The significant scheme was developed in the context of assessment research by Greene *et al.* (1989). They coded each article in terms of a primary and a secondary rationale (Bryman 2006). According to Bryman (2006), the scheme developed by Greene *et al.* (1989, p. 259) isolates five justifications for combining qualitative and quantitative research (Table 5.4). According to Bryman (2006), the "advantage of the Greene *et al.* (1989) scheme is its parsimony, in that it boils down the possible reasons for conducting multi-strategy research to just five reasons, although the authors' analysis revealed that initiation was uncommon" (p. 105). In this method, qualitative research is vital for understanding complex social phenomena, helping the researcher develop the theme from the respondents' points of view. Quantitative research summarises a large amount of data for generalisation purposes. The disadvantage is that it only allows primary and secondary data to be coded. For that reason, a more detailed but significantly less parsimonious scheme was devised. Bryman (2006) identified the second scheme with its rationales (see Table 5.4).

First scheme	
Triangulation	Convergence, corroboration, correspondence or results from different methods. In coding triangulation, the emphasis was placed on seeking corroboration between quantitative and qualitative data.
Complementarity	Seeks elaboration, enhancement, illustration, clarification of the results from one method with the results from another.
Development	Seeks to use the results from one method to help develop or inform the other method, where development is broadly construed to include sampling and implementation, as well as measurement decisions.
Initiation	Seeks the discovery of paradox and contradiction, new perspectives of [sic] frameworks, the recasting of questions or results from one method with questions or results from the other method.
Expansion	Seeks to extend the breadth and range of enquiry by using different methods for different inquiry components.
Second scheme	
Triangulation or greater validity	Refers to the traditional view that quantitative and qualitative research might be combined to triangulate findings in order that they may be mutually corroborated. If the term was used as a synonym for integrating quantitative and qualitative research, it was not coded as triangulation.
Offset	Refers to the suggestion that the research methods associated with both quantitative and qualitative research have their own strengths and weaknesses so that combining them allows the researcher to offset their weaknesses to draw on the strengths of both.
Completeness	Refers to the notion that the researcher can bring together a more comprehensive account of the area of enquiry in which he or she is interested if both quantitative and qualitative research is employed.
Process	Quantitative research provides an account of structures in social life but qualitative research provides a sense of process.
Different research questions	This is the argument that quantitative and qualitative research can each answer different research questions, but this item was coded only if authors explicitly stated that they were doing this.
Explanation	One is used to help explain findings generated by the other.
Unexpected results	Refers to the suggestion that quantitative and qualitative research can be fruitfully combined when one generates surprising results that can be understood by employing the other.
Instrument development	Refers to contexts in which qualitative research is employed to develop questionnaire and scale items – for example, so that better wording or more comprehensive closed answers can be generated.
Sampling	Refers to situations in which one approach is used to facilitate the sampling of respondents or cases.
Credibility	Refers to suggestions that employing both approaches enhances the integrity of findings.

Context	Refers to cases in which the combination is rationalised in terms of qualitative research, providing contextual understanding coupled with either generalisable, externally valid findings or broad relationships among variables uncovered through a survey.
Illustration	Refers to the use of qualitative data to illustrate quantitative findings, often referred to as putting 'meat on the bones' of 'dry' quantitative findings.
Utility or improving the usefulness of findings	Refers to a suggestion, which is more likely to be prominent among articles with an applied focus, that combining the two approaches will be more useful to practitioners and others.
Confirm and discover	This entails using qualitative data to generate hypotheses and using quantitative research to test them within a single project.
Diversity of views	This includes two slightly different rationales – namely, combining researchers' and participants' perspectives through quantitative and qualitative research respectively, and uncovering relationships between variables through quantitative research.
Enhancement or building upon quantitative and/or qualitative findings	This entails a reference to making more of or augmenting either quantitative or qualitative findings by gathering data using a qualitative or quantitative research approach.

Table 5.4: Justifications and rationale for combining quantitative and qualitative methods
Source: Adapted by Bryman (2006, pp. 105-107); Foroudi (2012)

Following the positivist perspective, an empirical investigation can be conducted to verify the conceptual model, to explain the main concept and generalise the research in a large sample by adopting the quantitative research (questionnaire) (Ageeva *et al.* 2018, 2019). Alternatively, researchers can begin with quantitative methods and move to qualitative research. This approach is similar to an example given by Creswell *et al.* (2003), where the key approach was a quantitative research, based on examining a theory but with a short number of qualitative interviews in the data collection phase of data collection. Figure 5.1 illustrates the procedures of mixed methods.

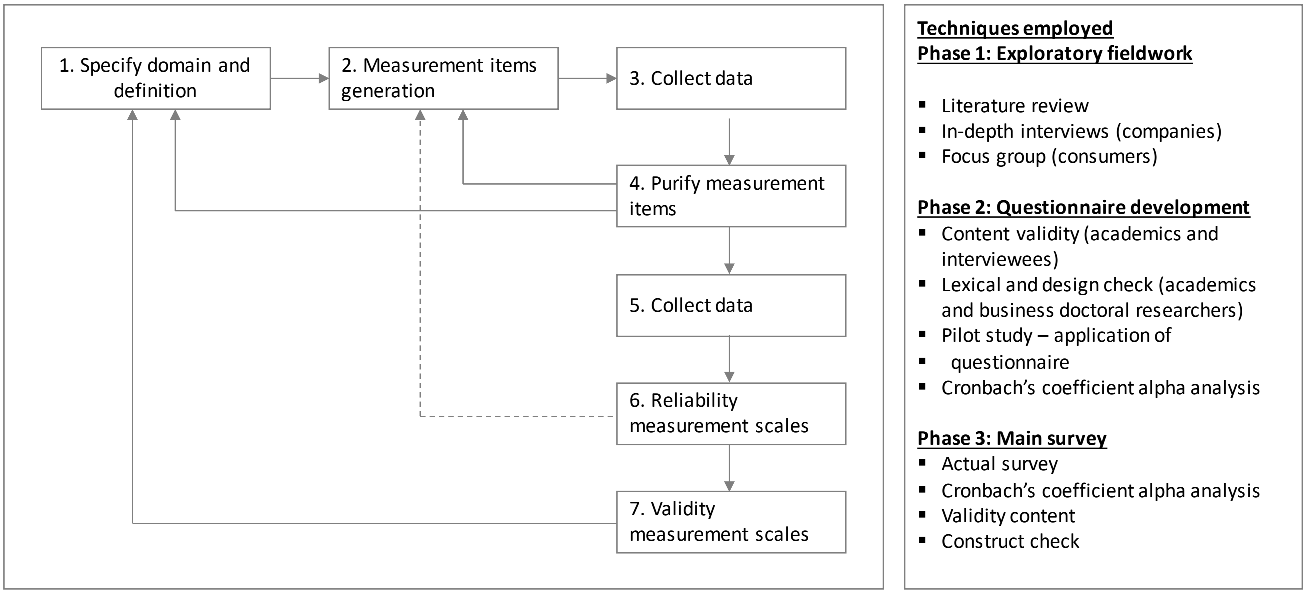
Take in Figure 5.1 here

Source: Based on Creswell *et al.* (2003, p. 235); Foroudi (2012)

To increase the validity of the study, an inductive approach can be used before the main survey and the qualitative data collection technique should be used to generate hypotheses and purify measures for the questionnaire (Deshpande 1983). Churchill (1979) and Foroudi *et al.* (2014) suggest a quantitative approach with multi-method engagement in the initial stages of an investigation. To examine the research's focal construct, quantitative methods are more suitable than the qualitative method. This method is more appropriate for theory testing rather than theory generation.

To measure the focal construct, it is suggested that researchers follow Churchill's (1979) approach for developing measures of multiple items for marketing constructs, and the approach of Gerbing and Anderson (1988) and DeVellis (2003) in order to construct a set of reliable and valid scales for establishing measurement reliability. This is expected to result in stronger relationships than the use of single-item measures. According to Churchill's (1979) theory, it integrates a qualitative paradigm while being predominantly quantitative in nature. Figure 5.2 illustrates the proposed steps in measurement scale development for marketing constructs. According to Churchill (1979), the first phase of research design is exploratory fieldwork.

Figure 5.2: Steps in measurement scale development



Source: Churchill (1979, p. 66); Foroudi (2012)

The first phase (Qualitative fieldwork)
An initial exploratory study can be carried out for the following reasons:

- To gain an in-depth understanding of the research area (Dacin and Brown 2002);
- To achieve insights into the research context;
- To understand the actual practice in the field in order to gauge whether the proposed research study was relevant;
- To obtain insightful information and understand the proposed research questions, generate hypotheses and purify measures for a questionnaire (Churchill 1979).

Churchill (1979) suggests that the exploratory study, known as an 'experience survey', consists of "a judgement sample of persons who can offer ideas and insights into the phenomenon" (p. 66). Exploratory studies tend to begin with a wide study and narrow down to study development (Saunders *et al.* 2007). Churchill (1979) suggests that certain techniques are used to generate sample items and reflect a construct (exploratory research, literature search, interview, and focus group).

In-depth interviews and group discussions are very useful (Foroudi *et al.* 2014, Ritchie *et al.* 2003) in bringing a new perspective to existing data (Ageeva and Foroudi 2019; Ritchie *et al.* 2003). The data collected from interviews and focus groups supplies information and insights and adds more data, that was not identified in the literature review. However, exploratory research rarely involves large samples (Malhotra and Birks 2000). To minimise any weaknesses, qualitative data can be used to construct a quantitative study, mainly in the form of a questionnaire (Churchill 1979). Table 5.5 illustrates the main benefit of using interviews and focus groups.

	In-depth interviews	**Focus groups**
Nature of data	For generating in-depth personal accounts	For generating data that is shaped by group interaction, refined and reflected
	To understand the personal context	To display a social context exploring how people talk about an issue

	For exploring issues in depth and in detail	For creative thinking and solutions, to display and discuss differences within the group
Subject matter	To understand complex processes and issues e.g.- Motivations, decisions-Impacts, outcomes	To tackle abstract and conceptual subjects where enabling or projective techniques are to be used, or in different or technical subjects where information is provided
	To explore private subjects of those involving social norms, for sensitive issues	For issues that would be illuminated by the display of social norms, for some sensitive issues, with careful group composition and handling
Study population	For participants who are likely to be willing or able to travel	Where participants are likely to be willing or able to travel to attend a group discussion
	Where the study population is geographically dispersed, where the population is highly diverse	Where the population is geographically clustered, where there is some shared background or relationship to the research topic
	Where there are issues of power or status	For participants who are unlikely to be inhibited by group setting
	Where people have communication difficulties	

Table 5.5: Application of in-depth interviews and focus groups
Adapted from Foroudi 2012, Ritchie et al. 2003

Planning, management and data interpretation of the qualitative stage

There are many approaches to qualitative data analysis, and these have been widely debated in the literature (Bazeley 2007, Bryman and Burgess 1994, Silverman 1993). One approach is to begin with grounded theory to test the data. To analyse the qualitative data, a process of coding should be used and guided by the conceptual framework developed using the literature. The researcher builds codes by creation of a shared understanding of the focal construct and its dimensions. This sets the framework for coding and analysing the data. The researcher determines that start codes address the research questions, hypotheses, problem areas, and/or key variables that the researcher identifies (Ageeva *et al.* 2019, Foroudi *et al.* 2014, Miles and Huberman 1994, p. 58).

Initially, coding of the narratives is based on the open codes process and the constructs identified in the literature review. According to Miles and Huberman (1994), the start list of codes should be based on a "conceptual framework, list of research questions, hypotheses, problem areas, and/or key variables that the researcher brings to the study" (p. 58). The researcher writes the memo for each interview transcript before coding the transcript. Coding the data makes it easier to search, to make comparisons and to identify any patterns that require further investigation. The process of coding data from interview transcripts situates the process as qualitative analysis (Andriotis *et al.* 2020; Weston *et al.* 2001). Under descriptive codes, the collected data should be gathered, and thematic ideas emerged with the data collected and related to the same content (Brown *et al.* 2019, Malhotra and Birks 2000, Lincoln and Guba 1985). According to Lincoln and Guba (1985), it is vital to "devise rules that describe category properties and that can, ultimately, be used to justify the inclusion of each data bit that remains assigned to the category as well as to provide a basis for later tests of replicability" (p. 347). The process ensures that the theoretical ideas that emerge from the first round of coding can be systematically shown in the data (Esterberg 2002). Codes are analysed in three stages of coding: open coding, axial coding, and selective coding (Esterberg 2002, Huberman and Miles 1994). The three stages of coding enhance improve the trustworthiness of the emergent data. The stages of the coding process are explained in Table 5.6.

The first stage of the data analysis is generation of open codes. The open codes are interpreted and categorised into higher concepts until the core categories emerged. The open code begins with reviewing the texts individually (interview transcripts), line-by-line, and highlighting passages where the focal construct and the relationships are discussed and coded using the starting list new open codes are formed during the process. Transcripts should read twice very carefully to find the patterns in the texts that are relevant to the literature. Each sentence should be compared with earlier sentences and with open codes for differences and similarities and differences. If the codes are the same or very similar, they are coded identically. If the codes are very dissimilar, the new sentence are coded using another separate label. The main aim of open coding is to find similar or different patterns in the texts, to the related literature review. Following open coding of each interview transcript, the researcher should read the open codes and write more comments and memos to make the analysis more rigorous. This results in the creation of the axial code.

Stages of the coding process	
Open coding	First stage, through which concepts are identified.
Axial coding	Second stage, through which second order categories are inductively derived from first order concepts generated during open coding
Selective coding	Final stage, through which emergent theory is identified and refined, and the emergent themes are integrated.

Table 16: The stages of coding process
Source: Foroudi (2012)

Axial coding is the second stage of data analysis and tries to establish the relationship and contrast between the core categories and sub-categories to enable the identification of patterns within the texts. Systematic axial coding is started after all open coding. Axial coding as a unique approach has the advantage of not misleading the data analysis. Axial codings are maximised by taking into account all of the open codes within one case. The procedure of axial coding is a process of constant comparison. Axial codes are generated based on differences and similarities of the collected data in open coding. After generating the axial code, the open codes are compared with each other and with the generated axial codes. This process assists the researcher to create a new axial code, change the existing axial codes, or merge them.

The final stage of coding is selective coding, which aims to integrate the emerging theory. Selective coding is the most complicated step of grounded theory analysis. To produce a theory that can eventually fit the data, the phenomena must be described in a way that is parsimonious (Strauss and Corbin 1998). According to Spiggle (1994), selective coding, "involves moving to a higher level of abstraction with the developed paradigmatic constructs, specifying relationships, and delineating a core category or construct around which the other categories and constructs revolve and that relates them to one another" (p. 495). Strauss and Corbin (1998) state that selective coding begins throughout the axial coding stage, by identifying the relationship betweenthese axial codes. This stage is the most difficult and confusing stage of grounded theory analysis, as it is needed to explain the phenomena but be parsimonious.

In addition to the standard theoretical coding process such as comparison, question asking and writing memos, the researcher employs extra three techniques:

- Reviewing the research questions as a general guideline;
- Re-considering the open codes and raw data while comparing axial codes,
- Discussing the codes with supervisors and experts, to identify the fitness and relationship between the codes.

By reviewing the data, the researcher should able to find out the dimensions of the focal construct, its main causes and its consequences. To produce a refined and complete synthesis and interpretation of the material collected, QSR NVivo software is appropriate for data administration and to achieve results. NVivo has tools for recording, data storage, retrieval and linking ideas and exploring the patterns of data and interpretation. It has a wide range of tools in a symmetrical, simple and accurate structure. The use of computer software helps to ensure rigour in the analytic process. NVivo allows the researcher to interrogate the data at a detailed level and addresses the validity and reliability of the study results and also ensures that the researcher works more methodically, thoroughly and attentively (Bazeley 2007). It makes data analysis more reliable, easier, more accurate and more transparent (Gibbs 2002), and manipulation and analysis of the data easier. It is useful for mapping out findings diagrammatically and assists the researcher with viewing the whole text, enabling the inter-relationships between codes to be seen easily (Edirisinghe *et al.* 2020, Foroudi *et al.* 2019, Welsh 2002). It is also useful for data storage and retrieval (Esterberg 2002).

The researcher should recognise the value of both manual and electronic tools in qualitative data analysis and management and use of both (Welsh 2002). The data should be checked against the content of specific nodes, as this could affect the inter-relationships of the thematic ideas, reviewing the nodes (themes) for consistency, and proceeding through the qualitative data analysis. To verify the reliability of the coding through content analysis, the code should be established more than once (Weber 1985) by another researcher, to gain their agreement on identification of the themes. Content analysis is a research technique for making replicable and valid inferences from data to its context. Patton (2001) states, "the qualitative analyst's effort at uncovering patterns, themes, and categories is a creative process that requires making carefully considered judgments about what is really significant and meaningful in the data" (p. 406). The coding system is used to analyse each word and phrase, allowing consideration of possible meanings assumed or intended by the speaker (Palazzo *et al.* 2020, Weston *et al.* 2001). The researcher should try to locate the phenomenon within the data, and mark where the phenomenon begins and ends (Weston *et al.* 2001), based on a prior research-driven code development approach (Patton 2001, Strauss and Corbin 1998). The researcher may collect 'rich' data in the form of verbatim transcripts of all interviews with each interviewee, providing the information needed to test the developing scales. This allows consistency of terminology and consistency with previous work. It also facilitates explanation of the data using the relevant research framework.

Validity and reliability

The quality of the data is significant in social sciences because of the diverse philosophical and methodological approaches that are taken to the study of human activity (Ritchie *et al.* 2003). Validity and reliability contribute to designing a study, analysing its results and judging its quality. However, there is no common definition of reliability and validity in qualitative research. To certify the reliability of the research, an assessment of 'trustworthiness' is needed. The notion of determining truth through measures of reliability and validity is substantiated by the idea of trustworthiness (Lincoln and Guba 1985). Seale (1999) states that the: "trustworthiness of a research report lies at the heart of issues conventionally discussed as validity and reliability" (p. 266). A theoretical sample rather than a statistically random sample can "maximise opportunities for comparing concepts along their properties for the similarities and differences enabling researchers to define categories, to differentiate among them, and to specify their range of variability" (Strauss and Corbin 1998, p. 149). As Lincoln and Guba (1985) stated, "there is no validity without reliability, an expression of the former validity is sufficient to establish the latter reliability" (p. 316). Reliability means sustainable results and validity means the research is well-grounded in the data. Reliability addresses how accurately the research methods and techniques produce data and is a consequence of the validity in a study (Patton 2001). Table 5.7 presents the techniques could improve the trustworthiness.

Traditional criteria	Trustworthiness criteria	Techniques employed to ensure trustworthiness
Internal validity	Credibility	Quality access (researcher was provided with an office desk, computer, access to company intranet, email address, freedom of talking to and interviewing anybody, freedom of getting any company documents, including lots of confidential strategic documents) and extensive engagement in the field
		Multiple triangulations
		Peer debriefing
		Constant comparison
External validity	Transferability	Detailed description of the research setting
		Multiple cases and cross-case comparison
Reliability	Dependability	Purposive and theoretical sampling
		Cases and informant confidentiality protected
		Rigorous multiple stages of coding
Objectivity	Confirmability	Separately presenting the exemplar open and axial codes.
		Word-by-word interview transcription
		Accurate records of contacts and interviews
		Writing research journal
		Carefully keeping notes of observation
		Regularly keeping notes of emergent theoretical and methodological ideas

Table 5.7: Meeting the criteria of trustworthiness
Source: Foroudi 2012, Lincoln and Guba 1985

To examine how the validity and reliability of a study are affected by the qualitative researchers' perceptions and hence to eradicate bias and increase the study's truthfulness, the triangulation method is used. Creswell and Miller (2000) describe triangulation as: "a validity procedure where researchers search for convergence among multiple and different sources of information to form themes or categories in a study" (p. 126). Triangulation improves the validity and reliability of a study and evaluation of its findings. Reliability, validity and triangulation are approaches to establishing truth. To verify the reliability of coding through content analysis, stability is ascertained when content is coded more than once (Vollero *et al.* 2020; Weber 1985). To assess the reliability of emergent categories of the focal construct, one independent coder with considerable qualitative research experience but unfamiliar with the study should be employed.

Interviews
To meet the research objectives, the research should start with interviews, to identify and operationalise the main elements to measure the focal construct. In-depth interviews can generate a deeper understanding of the subject and collect attitudinal and behavioural data (Foroudi *et al.* 2014, Shiu *et al.* 2009). A topic guide helps to outline the focal construct as the topic of interest, balance the interview with the key topics and encourage continuity in discussions. The interview can be conducted via face-to-face or digitally, to establish a clear overview of the focal construct and allow deeper understanding of the research objective. The interviews can take place in a location chosen by the participant (Ritchie *et al.* 2003). Usually, interviewers decide the venues and timing of interviews. The interview should be recorded and transcribed verbatim to ensure reliability (Andriopoulos and Lewis 2009). The in-depth interview technique can unveil fundamental

motivations, beliefs, attitudes and feelings about the topic. A question sheet should be designed to check whether all the areas of interest are covered during the interviews.

Researchers should observe a professional dress code and presented themselves as researchers (Easterby-Smith *et al.* 2002). The researcher should develop trust with the respondents through different approaches. In-depth interviews give researchers "the opportunity for the researcher to probe deeply to uncover new clues, open up new dimensions of a problem and to secure vivid, accurate inclusive accounts that are based on personal experience" (Burgess 1982, p. 107). In-depth interviews are flexible and allow questions to be asked on a wide variety of topics. According to Sekaran (2003), personal interviews are extensively used in marketing studies and help to ensur that respondents have understood the questions.

Qualitative studies are based on non-quantified data, such as values, perceptions and attitudes. Attitude is a significant concept often used to understand and predict people's reaction to an object or change. Direct questions can be designed as a fixed-response alternative question that requires selecting from a predetermined set of responses, to measure a dimension of attitude (Malhotra and Birks 2000). The obtained data is "more reliable because the responses are limited to the alternatives stated" (Malhotra and Birks 2000, p. 210).

Marketing scholars should place more emphasis on exploratory research and first embark on a situation analysis via interviews with company managers (Churchill 1979; Foroudi *et al.* 2014). Marketing researchers adopt a qualitative approach ,to be able to explore in-depth issues in a less structured format and encapsulate the experiences, feeling and beliefs of the respondents in their study (Malhotra and Birks 2000).

Focus groups

Focus groups can be used to understand perceptions about the research. When little is known in advance of investigation, data collected from focus group provided extensive information in a limited time. Focus groups are an an effective way of gathering information, testing assumptions or generating information about the research topic, helping the researcher gather information in a shorter time than one-to-one interviews, with the added bonus of the group dynamic. The researcher can be alerted to new ideas. Employing focus group allows the researcher to gain further insights into what people think about the research (Churchill 1979; Fern 1982; Krueger 1994). Focus groups are used for the following reasons (Fern 1982, p. 1):

- "People are a valuable source of information";
- "People can report on and about themselves, and that they are articulate enough to verbalise their thoughts, feelings, and behaviors";
- "The facilitator who 'focuses' the interview can help people retrieve forgotten information";
- "The dynamics in the group can be used to generate genuine information, rather than the "group think phenomenon";
- "Interviewing a group is better than interviewing an individual";
- "Identifying and pretesting questionnaire items".

The venues and timing of focus group interviews can be decided by participants. The researcher should try to provide an environment conducive to respondents feeling comfortable expressing their opinions (Malhotra and Birks 2000). Group discussions provide safety in numbers, allowing participants to communicate more fully (Ritchie *et al.* 2003). The focus group can benefit from diversity in group composition (Churchill 1979, Krueger 1994). To deal with group member(s) dominating the research discussion, the researcher should encourage each group members to speak. Smithson (2000) defined focus group as a 'collective voice' which means "a group process of collaboratively constructing a joint perspective, or argument, which emerges very much as a collective procedure which leads to consensus, rather than as any individual's view" (p. 109). The focus group interviews should be recorded and transcribed verbatim. The transcriptions shoulbe d cross-checked with the second recorder. For reasons of confidentiality, the names of participants are replaced with a code.

The second phase (research instrument and scale development)
The aim of this phase is to develop valid and reliable measures of the theoretical construct through synthesising insight from the existing literature and qualitative study. When many items are produced in the first phase, some may be identical or equivalent items, and for so they are excluded for the sake of parsimony. Some academics assess items generated from qualitative research and remove unnecessary measures, to ensure that these items are representative of the scale's domain.

Specifying the domain constructs
Specifying the content domain is usually achieved via relevant literature and qualitative studies - the first stage in questionnaire development. When there are few studies of the topic the researcher can follow Churchill's (1979) paradigm, to generate a set of constructs, from the literature, from interviews and researchers that capture the domain of the constructs. For better measurement, the operational definition and dimensions of the focal construct should be specified.

Generation of measurement items
Measurement item generation is the second step in Churchill's (1979) paradigm. The following recommendation by DeVillis (2003, pp. 66-70) can be used to develop the scale:

- Avoid exceptional length;
- Ensure readability of each item;
- Avoid double-barrelled items;
- Avoid ambiguous pronoun references;
- Use positive and negatively worded items.

To generate the measurement items, the researcher should use a combination of literature and a qualitative study (i.e. semi-structured interviews with experts and focus groups with academia) (Churchill 1979; Foroudi *et al.* 2014). The items representing each construct are a multi-item scale and regenerated from existing literature.

According to Churchill (1979), the single items usually have considerable "uniqueness or specificity in that each item seems to have only a low correlation with the attribute being measured and tends to relate to other attributes" (p. 66). Single items may have significant measurement errors and can produce "unreliable responses in the same way so that the same scale position is unlikely to be checked in successive administrations of an instrument" (Churchill 1979, p. 66). According to Churchill (1979), a multi-item scale should be used for each construct. Researchers (Churchill 1979; Kotabe 1990, Peter 1981, Zaichkowsky 1985) have highlighted the need for explicit attention to be paid to examining the reliability and validity of measurement. The researcher should create reliable and valid scales based on previous studies, but keep them to a minimum to avoid redundancy in the measures and a lengthy questionnaire.

Purifying measurement scales
Purifying measurement scales is the third step of Churchill's (1979) paradigm. Purification is related partly to the measurement model used (Churchill 1979, Foroudi 2019, 2020). Validity is "the degree to which what the researcher was trying to measure was actually measured" (McDaniel and Gates 2006, pp. 224-227). Two types of validity are needed before conducting the main survey: face validity and content validity. Both are subjective in nature and provide an indication of the adequacy

of the questionnaire. According to Kerlinger (1973), content validity is judgmental and refers to “the extent to which a specific set of items reflects a content domain” (DeVellis 2003, p. 49).

To assess the content validity of questionnaire items, he judgement of experts and academics familiar with the topic can be used (Bearden *et al.* 1993; Zaichkowsky 1985). They are required to comment on the suitability of the items and check the clarity of wording, to check importance of each statement and to indicate which items should be retained. They should be asked to judge whether the items used in the instrument are representative of the area being investigated, whether the questionnaire items measure what they are intended to measure, perhaps by testing the questionnaire by completing it, also checking the wording, layout, and ease of competing. Academics can act as judges of a scale’s performance in previous studies. The results of this procedure reflect the ‘informed’ judgments of experts in the content field (Green *et al.* 1988). The summary of benefits and limitations of content analysis is illustrated in Table 5.8.

Benefits	**Limitations**
Flexibility of research design i.e. types of inferences	Analyses the communication (message) only
Supplements multi-method analyses	Findings may be questionable alone, therefore, verification using another method may be required
Wide variety of analytical application	Underlying premise must be frequency related
May be qualitative and/or quantitative	Reliability – stability, reproducibility, accuracy of judges
May be automated – improves, reliability, reduces cost/time	Validity – construct, hypothesis, predictive and semantic
Range of computer software developed	Less opportunity to pre-test, discuss mechanism with independent judges
Copes with large quantities of data	Undue bias if only part data is analysed, possibly abstracting from context of communication
Unobtrusive, unstructured, context sensitive	Lack of reliability and validity measures reported, raising questions of credibility
Development of standards applicable to specific research, e.g. negotiations	

Table 5.8: Summary of benefits and limitations of content analysis
Source: Foroudi (2012); Harwood and Garry (2003, p. 493).

Malhotra and Birks (2000) state that a questionnaire should be pilot tested first, to refine the questionnaire so that respondents have no difficulty answering (Saunders *et al.* 2007). The scale needs to be tested. The Likert scale is commonly used, often with 5 or 7 points (e.g. 1 = strongly disagree, 5 or 7 – strongly agree (Foroudi 2019; 2020; Foroudi *et al.* 2020), with 7 points recommended to increase construct variance and reduce measurement error (Churchill and Peter 1984; Foroudi *et al.* 2014). The Likert scale usually is satisfactory in relation to the underlying distribution of responses (Bagozzi 1994). Based on the results of the quantitative assessment, the items can be adjusted and submitted to scale purification.

Quantitative assessment: pilot study

After qualitative assessment, the questionnaire can be revised for use in the actual survey (Foroudi *et al.* 2014; Malhotra and Birks 2000), to ensure the constructs are valid and the measurement scales are reliable (Saunders *et al.* 2007).

Pilot study

The pilot study aims to assess the requirements for instrument purification e.g. testing questions wording, sequence, form and layout, question difficulty and instruction, familiarity with respondents, response rate, questionnaire completion time and analysis process (Denscombe 2007, Malhotra and Birks 2000, Ticehurst and Veal 2005). According to Malhotra and Birks (2000), the pilot study sample should be 20 to 40 respondents in a small-scale test (Malhotra and Birks 2000). The respondents in the pilot study should not be invited to participate in the final study, as previous participation may affect their responses (Haralambos and Holborn 2000).

The purpose of the pilot study is to clarify the questionnaire so that there are no ambiguously formulated items (Welman and Kruger 2001), that respondents can easily answer the questions, that there are no errors or problems in recording data (Saunders *et al.* 2007, Peter 1979). And to validate the timing and clarity of the survey, the reliability of the constructs, and to carry out manipulation checks (Malhotra 1999).

Reliability relates to whether a set of variables is consistent in terms of what it is intended to measure and iss assessed via Cronbach's alpha (Cronbach 1951). Before conducting the main survey, it is important that the measures used are investigated for reliability (Foroudi *et al.* 2014). Reliability is a precondition of validity. Exploratory factor analysis (EFA) is performed in the pilot study to reduce the number of questionnaire items and identify any pattern in the data (De Vaus 2002). A Cronbach's alpha value greater than 0.70 shows high suitabiltiy for most research purposes (De Vaus 2002; Foroudi *et al.* 2014, Hair *et al.* 2010, Nunnally 1978).

Exploratory factor analysis (EFA) is a practical scale for reducing the numbers of observed variables (indicator) to a smaller and more controllable set, by examining the factorial structure of scales taking into account three assumptions underlying EFA - absolute sample size, correlation coefficients and sampling adequacy (Hair *et al.* 2010). This analysis is to make sure that the individual items are loaded onto corresponding factors as intended.

After deleting superfluous items, the researcher should carry out a reliability test to assess whether the constructs, especially the revised items, yield useful results, the "measures are free from random error" and "provide consistent data" (McDaniel and Gates 2006, p. 222). Examining how respondents answer the survey questions/items related to the constructs in the conceptual framework is important, particularly where the questionnaire examines psychometric properties, which require acceptable reliability and validity (Churchill 1979, Hair *et al.* 2010),

A reliability test is used for the evaluation of consistency between those measurement items measuring single variables (spilt-half method) (Hair *et al.* 2010). This involves correlating the same respondent's score on the same measurement item at two different points in time (test-retest) (Ticehurst and Veal 2005). Reliability helps establish accuracy and consistency of measures, nbias avoidance and reproducibility in different samples and time horizons. Cronbach's α coefficient method is the favourite statistical methods to measure reliability, as it is easy to calculate and is well-accepted in academic research (Cronbach 1951, Nunnally 1978, Tabachnick and Fidell 2007).

Main survey

Target population and sampling

"The segment of population that is selected for investigation is defined as the sample" (Bryman and Bell 2007, p. 182). The larger group of which the sample is a subset is called the 'research population'. Bryman and Bell (2007) define population as the universe of units (people, nations, cities, regions, firms etc.) from which the sample is to be selected. The group of subjects the investigator actually studies (or collects data on) is the sample, a set of elements selected from a population (Malhotra and Birks 2000) that represents the main area of research and is presumed to have a high external validity (Churchill 1999, Foroudi *et al.* 2018, 2019, 2020). Sample design may be biased due to sampling frame error, population specification error and selection error (McDaniel and Gates 1993).

The main reason to sample is to save money and time. The sample should be representative of its population, allowing the researcher to make inferences or generalisations from the sample to the population. However, if sample size is too low, it may not offer reliable answers to the study questions. Sample size of any research must be determined during the design stage. Salant and Dillman (1994) state that the sample should be determined by four main factors:

- How much sampling error can be tolerated;
- Population size;
- How varied the population is with respect to the characteristics of interest;
- The smallest subgroup within the sample for which estimates are required.

There are two main sampling methods, probability and non-probability. A probability sample is selected using random selection, so each population unit has a known chance of selection. This makes the sample more likely to be representative and to keep sampling error low. A non-probability sample has not been selected using a random method, so some units in the population are more likely to be selected. However, in management, convenience samples (simply ones where respondents are chosen based on their ease of inclusion – often used in pilot studies) are common.
A survey rarely achieves a response from every contact (Denscombe 2007), and in many web-based surveys the number of contacts exposed to the questionnaire is unknown, so there is a strong possibility of bias introduced by self-selection, Churchill (1999) suggests that face-to-face questionnaire collection is the most used sampling methods in large-scale surveys. It also guarantees that the questionnaire is completed by the respondent who was targeted. Non-probability 'snowballing' can be used as a distribution method by asking the initial informants to suggest others (Andriopoulos and Lewis 2009, Bryman and Bell 2007, Goodman 1961, Miles and Huberman 1994, Shiu *et al.* 2009, Stevens *et al.* 1997, Zinkhan *et al.* 1983). According to Stevens (1996) a sample should be more than 300 respondents. Bentler and Chou (1987) state that five cases per parameter is acceptable when the data is perfectly distributed and has no missing or outlying cases. Armstrong and Overton (1977) identify that non-response bias "involves the assumption that people who are more interested in the subject of a questionnaire respond more readily and that non-response bias occurs on items in which the subject's answer is related to his interest in the questionnaire" (p. 2).

Appropriate number of participants
The main considerations that determine the number sampled are related to the data analysis processes or techniques (Hair *et al.* 2010) and obtain reliable estimates (Raykov and Widaman 1995) are the 'multivariate distribution of the data'. In the case of non-normal data, the ratio of respondents to parameters needs to be higher (i.e. 15:1). In other words, 5 respondents for each parameter is an acceptable number to minimise deviation from normality. If the researcher is using the maximum likelihood (ML) method, the sample size is 150-400 responses. If the researcher is using structural equation modelling (SEM), which is based on the maximum likelihood estimation (MLE) method, the sample size should be 150 to 400 respondents. However, if the sample size exceeds 400, the MLE method becomes more sensitive and the results of goodness-of-fit measures become poorer (Hair *et al.* 2010). 3).

For 'model complexity', the sample size should be as follows:

- SEM with five or fewer constructs can be estimated with a small sample size of 100 to 150, if each construct is measured by more than three items and the item communalities are higher than 0.6;

- If any of the communalities are modest (0.45 to 0.55) or the model includes a construct with fewer than three items, the required sample size is 200 (Hair *et al.* 2010).
- If the number of factors in the model is more than six, some constructs are measured by fewer than three items and the communalities are low, a large sample size perhaps exceeding 500 is required;
- Missing data', if more than 10% of data is expected to be missing, sample size should be increased
- Average error variance of indicator: larger sample sizes are required when constructs commonalities are smaller than 0.5.

Roscoe (1975) recommends these rules of thumb for selecting sample sizes based on acceptable confidence levels in behavioural research studies.
- Sample sizes larger than 30 and less than 500 are appropriate for most research;
- If researchers have more than one group (e.g. male and female), researchers need more than 30 participants for each group
- If researchers use multivariate analysis, the sample size should be at least 10 times or more the number of variables used in the analysis. Stevens (1996) suggests 15 cases per construct to get trustworthy results. Bentler and Chou (1987) advised that if the data is normally distributed, at least five cases per parameter are sufficient;
- If researchers are conducting a simple experiment, the appropriate sample size should be ten to 20 participants.

Comrey and Lee (1992) state that a sample size of 50 is very poor ,100 is poor 200 is fair, 300 is good, 500 ai very good, and 1,000 is excellent.

Data analysis techniques and statistical packages

Data analysis consisted of three stages. In the first stage, the content and the scales should be refined based on the collected information from the qualitative and quantitative data. The second stage is to validate the scales based on the quantitative data from the main survey. The third stage is to test the final model.

According to Churchill (1979), multi-item scale development is used for each construct to increase reliability and decrease measurement error. Churchill (1979) suggests using multi-item scales rather than single-item scales. Exploratory factor analysis (EFA) should be performed in the pilot study and the main study to reduce the items and identify any pattern in the data (Tabachnick and Fidell 2007). The alpha coefficient should be checked in the quantitative data to assess the reliability of the scale and quality of the instrument (internal consistency) (Churchill 1979; Peter 1979).Confirmatory factor analysis (CFA) should be carried out on the main survey data to assess the measurement properties of the existing scales' validity (Hair *et al.* 2010). This is useful if scales needed to be constructed for additional examination in structural modelling and applied to confirm the theory of the latent variables (Hair *et al.* 2010). Structural equation modelling (SEM) is used to test the hypotheses (Hair *et al.* 2010) and to avoid possible connections among structural models and measurements.

The use of SPSS (Statistical Package for Social Sciences) has been confirmed by many researchers (Field 2009; Tabachnick and Fidell 2007). SPSS can be used at the initial stage of data analysis (Norusis 1999; 1993) can for several purposes:
- Coding, editing and checking missing data;
- Checking the assumptions of normality, linearity, multi-collinearity, and outliers (examining skewness and kurtosis);
- Demonstrating the central tendency and dispersions of the variables, the mean, the standard deviation, and analysing frequencies were calculated;

- Exploratory factor analysis and descriptive analysis using an overview of the sample (Tabachnick and Fidell 2007);
- Applying reliability tests to the data to assess the validity, reliability and dimensionality of the instrument (Churchill 1979, Peter 1979). The reason for the test is to assess the scales used to measure the constructs and refine the measures (Churchill 1979).

Analysis of Moment Structure (AMOS), a unique graphical interface, should be used to determine the quality of the proposed measurement model and hypothesised structural model. It should be used to perform the confirmatory factor analysis (CFA) and structural modelling (Byrne 2001).

Exploratory factor analysis (EFA) and coefficient alpha

Exploratory factor analysis (EFA) analysis is a fundamental and useful technique for the early stages of the scale validity (Netemeyer *et al.* 2003). EFA is a data-driven (exploratory approach) and is a practical scale for reducing the numbers of observed variables (indicator) to a smaller and more controllable set (Anderson and Gerbing 1988; Hair *et al.* 2010).

Hair *et al.* (2010) state that exploratory factor analysis ensures that "any individual factor should account for the difference of at least one single variable" (p. 103). It helps the researcher to identify factors that are independent of each other, allowing the structure of a specific field to be understood (Hair *et al.* 2010). The purpose of EFA is to explore the data and provide information to the researcher about the number of possible factors that best represent the data (Hair *et al.* 2010). EFA is useful as an initial analytical technique to prepare data for SEM (Steenkamp and Trijp 1991). The items for each construct should be examined before performing the factor analysis and reliability test. EFA can be performed in the pilot as well as the main study, to reduce the items and identify any pattern in the data (De Vaus 200; Tabachnick and Fidell 2007). It inspects the factor structure of every variable in the conceptual framework and can be used to propose the dimensions connected with the underlying constructs (Churchill 1979).

The principal components method should be applied for factor extraction (Hair *et al.* 2010; Tabachnick and Fidell 2007). This method examines the total variance (i.e. common, unique and error variances) to predict the minimum number of factors necessary to explain the maximum amount of variance. An orthogonal Varimax rotation method is particularly suitable for reducing the number of variables to a smaller group of uncorrelated variables. These variables are then used in prediction (Hair *et al.* 2010). Eigenvalues are used to identify the number of factors to extract (Hair *et al.* 2010; Nunnally and Bernstein 1994) and defined on the latent root criterion (eigenvalue >1.00).

Structural equation modelling (SEM)

To gain insight into the various influences and relationships, SEM should be used to separate relationships for each dependent variable (Foroudi *et al.* 2014; 2020; Hair *et al.* 2010). According to Tabachnick and Fidell (2007), SEM is a collection of statistical techniques that allow a set of associations between one or more independent variables, either continuous or discrete, and one or more dependent variables, either continuous or discrete, to be examined. Exogenous variables and endogenous variables can be either factors or measured variables.

SEM is also referred to as causal modelling, causal analysis, simultaneous equation modelling, analysis of covariance structures, path analysis, or confirmatory factor analysis. The latter two are special types of SEM (Tabachnick and Fidell 2007). SEM can be used for the following reasons (Hair *et al.* 2010, Tabachnick and Fidell 2007):

- When the phenomena of interest are complex and multidimensional, SEM is the only analysis that allows several complete and simultaneous dependent associations between observable indicators and the latent variable (i.e. by using the measurement model) and testing of associations among latent variables (i.e. by using the structural model) by calculating multiple regression equations

- When SEM analysis is the specification of a model, so this is a confirmatory rather than an exploratory technique.
- When the researcher needs to calculate unidimensionality, reliability and validity of each construct individually.
- When the researcher needs to estimate direct and indirect correlation
- When explicit estimates of measurement errors are required or when hypothesis testing is required for inferential purposes.
- When latent variables are needed to account for measurement error to provide the overall goodness-of-fit to test the measurement model.
- When the researcher needs to answer questions that involve multiple regression analyses of factors (Foroudi 2019; 2020; Nazarian *et al.* 2017; 2019).

Stages in structural equation modelling

The first stage tests the measurement properties of the underlying latent variables in the model using confirmatory factor analysis for each construct. The measurement model explains the causal relations among the observed indicators (variables) and respective latent constructs (variables) (Anderson and Gerbing 1982, Chau 1997) to the unidimensionality assumption. Unidimensionality is assessed by the overall fit of the confirmatory model (Garver and Mentzer 1999). Unidimensionality refers to a set of indicators that has only one underlying construct (Hair *et al.* 2010). Confirmatory factor analysis examines another important property, the original unidimensionality of a scale and is developed by EFA (Steenkamp and Trijp 1991). A confirmatory measurement model should be used at this stage to classify the strong association between observed variables and respective constructs (Anderson and Gerbing 1988) to ensure that the standardised factor loading values are greater than 0.6 or above. Confirmatory factor analysis is computed to examine whether each subset of items is internally consistent (Foroudi 2019). The validity and reliability of the construct is significant for further theory testing. After EFA, CFA allows the computation of an additional estimation of a construct's reliability, namely composite reliability (Gerbing and Anderson 1988, Hair *et al.* 2010).

At the second stage, a structural model can be used to test the development of a measurement that confirms the relationships between a construct and its indicators and to examine the structural model and the casual connection among latent constructs (Anderson and Gerbing 1982). The constructs may all be measured by latent variables, by observed variables or by a combination of the two.

Evaluating the fit of the model

CFA contributes to the confirmatory stage, giving total control over a construct's indicators, allowing a statistical test of goodness-of-fit and dimensionality for the specific measurement model (Hair *et al.* 2010). The purpose of the CFA is to validate/confirm the measurement factors that exist within a set of variables involved in the theoretical model (Hair *et al.* 2010). According to Bollen (1989), assessing reliability usually assumes unidimensional measures. Novick and Lewis (1967) state that coefficient alpha, the customary index of reliability in marketing, underestimates the reliability of a multidimensional measure. Unidimensionality is required for the effective use of the coefficient alpha (Hunter and Gerbing 1982) and to evaluate the goodness-of-fit of any model that considers theoretical, statistical, and practical deliberations. As recommended in the methodological literature on CFA, incremental fit indices and indices of model parsimony should be used. Absolute fit indices can be used to examine the structural model and measurement models (Hair *et al.* 2010). Absolute fit indices indicate how far the hypothesised model reproduces the sample data. The goodness-of-fit indices are used to examine the nomological validity of the measurement models. Absolute fit indices do not use an alternative model as a base for comparison.

Chi-squared ($\chi2$) is the most common method of evaluating goodness-of-fit. Chi-squared statistics iare the first measure of fit included in the Amos output. As Hair *et al.* (2010) cited that a low $\chi2$ value, indicating no significance, would indicate good fit, because the chi-square test is used to measure actual and predicted matrices and non-significance means that there is no significant difference among the actual and predicted matrices. In terms of a model's goodness-of-fit, p-values specify whether the model is significantly different from the null model. In statistics, the null is usually '0'. A low p-value or one close to zero is taken as evidence that the null hypothesis can be 'rejected' with a low probability of being wrong in reaching that conclusion (MacLean and Gray 1998). The discrepancy between the two matrices should not be statistically different ($p>.05$). Hair *et al.* (2010) and Tabachnick and Fidell (2007) state that using this fit to assess the overall goodness-of-fit of the model has been criticised as chi-squared is very sensitive to the sample size.

Kline (1998) suggested that a $\chi2$/ d.f. ratio of 3 or less indicate reasonable fit of the model. The $\chi2$ is very sensitive to sample size, particularly if the observations are greater than 200. When the data demonstrates deviations from normality, the chi-squared is larger than what is expected from error in the model. There are no clear-cut guidelines for the minimum acceptable norm. Chi-squared is the original fit index for SEM and should be combined with other indices (Hair *et al.* 2010). Chi-squared is routinely reported in SEM results.

The goodness-of-fit index (GFI) was introduced by Joreskog and Sorbom (1982) and the first measure of model to create a fit statistic that is less sensitive to sample size. The GFI produces the relative amount of variance and covariance in the sample covariance matrix, the population covariance matrix. GFI values range from zero to one, with values close to one being indicative of a good fit. If the index is greater than one, it is set at one and if less than zero, it is set to zero. The GFI should be between 0.90 and 1.00. Values between 0.80 and 0.89 are indicative of a reasonable fit (Doll *et al.* 1994).A GFI with less than 0.8 should be discarded.

The adjusted goodness-of-fit Index (AGFI) is useful for comparing competing models and is adjusted for the degrees of freedom of the model to the degrees of freedom for the null model (Hair *et al.* 2010). The GFI and AGFI are chi-squared-based calculations independent of degrees of freedom. AGFI adjusts the GFI for degree of freedom, resulting in lower values for models with more parameters. The AGFI corresponds to the GFI in replacing the total sum of squares by the mean sum of squares. The adjusted goodness-of-fit index should be greater than 0.90, which indicates an adequate fit (Bentler and Bonett 1980). AGFI values range from zero to one with values equal to or greater than 0.9 considered to be a good fit (Byrne 2001, Hair *et al.* 2010, Tabachnick and Fidell 2007). Values between 0.90 and 1.00 are considered a good fit. Values ranging from 0.80 to 0.89 indicate a reasonable fit (Doll *et al.* 1994).

Root-mean square error of approximation (RMSEA) measures the discrepancy between the sample and fitted covariance matrices (Steiger 1990) and is sensitive to the number of parameters (MacCallum *et al.* 1996). According to Hair *et al.* (2010), RMSEA represents how well a model fits a population (p. 748). A value of less than 0.05 indicates good fit, up to 0.08 reasonable fit, morethan 0.08 poor and unacceptable fit (Byrne 2001, Hair *et al.* 2010, Tabachnick and Fidell 2007).

Incremental fit indices calculate how a specified model fits a specific null model (Hair *et al.* 2010). The normed fit index (NFI) or Bentler-Bonett index compares nested models (Tabachnick and Fidell 2007). NFI compares the model with the recommended model without considering degrees of freedom. NFI measures how much a model is improved in terms of fit compared with the base model (Hair *et al.* 2010). NFI compares the $\chi2$ value of the model to the $\chi2$ value of the independence model (Byrne 2001, Hair *et al.* 2010, Tabachnick and Fidell 2007). However, NFI does not control for degrees of freedom and underestimates the fit in small samples (Byrne 2001). CFI is considered to be an improved version of the NFI (Byrne 2001, Hair *et al.* 2010, Tabachnick and Fidell 2007).

The comparative fit index (CFI) is directly based on the non-centrality measure. If it is greater than one, it is set at one and, if it is less than zero, it is set to zero. A CFI close to one is considered to be a good fit (Bentler 1990). CFI depends on the average size of the correlations in the data (Byrne 2001; Hair *et al.* 2010; Tabachnick and Fidell 2007). If the average connection among variables is not high, then the CFI will not be very high.

The Tucker-Lewis index (TLI), also known as non-normed fit index (NNFI), compares the $\chi 2$ value of the model with that of the independence model and takes degrees of freedom for both models into consideration (Byrne 2001, Hair *et al.* 2010, Tabachnick and Fidell 2007). The Tucker-Lewis index (TLI) depends on the average size of the correlations in the data. If the average relationship among variables is not high, then the TLI will not be very high. It is a mathematical comparison of a particular theoretical measurement model and a baseline null model (Hair *et al.* 2010). A value of 0.9 or higher is considered good and a value of 0.8 is considered acceptable (Gerbing and Anderson 1992). TLI is an example of an index that adjusts for parsimony, even though that was not its original intent. The results of the best fitting model are shown in Table 5.9.

	Type	**Acceptance level in this research**
Coefficient alpha (α)	Unidimensionality	α > 0.7 adequate and > 0.5 acceptable
Standardised Regression Weight ()		Beta > 0.15
Chi-square (with associated degrees of freedom and probability of significant different) (df, p)	Model fit	p > 0.05 (at α equals to 0.05 level)
Normed chi-square (/df)	Absolute fit and model parsimony	< /df < 3.0
Normalised fit index (NFI)	Incremental fit Compare model to baseline independence model	Values above 0.08 and close 0.90 show acceptable fit
Non-normalised fit index (NNFI)		
Comparative fit index (CFI)		
Goodness-of-fit index (GFI)	Absolute fit	0.90
Adjusted goodness-of-fit (AGFI)		0.90
Root mean square error of approximation (RMSEA)		0.08

Table 5.9: Results of the best fitting model
Source: Developed from Foroudi (2012), Hair et al. (2010)

Unidimensionality
Unidimensionality is a significant property for measures because it is essential but not adequate for construct validity (Gerbing and Anderson 1988). As defined by Cronbach (1984), "A set of items is 'unidimensional' if their order of difficulty is the same for everyone in a population of interest" (p. 116). A unidimensional item (indicator) has only one underlying construct, and Anderson and Gerbing (1988) state a unidimensional measure consists of unidimensional items or indicators. Unidimensionality is typically assumed in the specification of a model estimated with structural equation analysis, to separate measurement issues (i.e. the association between a construct and its

observed variables or indicators) from model structural issues (i.e. the associations or paths between constructs) (Anderson and Gerbing 1988).

Anderson and Gerbing (1982) proposed operationalising unidimensionality by using the structural equation analysis notions of external and internal consistency. Consistency has been described as the structural equation model to fit the data (Kenny 1979). Consistency iss defined by Anderson and Gerbing (1982) as two indicators of X, x1 and x2, which are internally consistent whether the correlation among them is the same as the correlations with their construct X. Correspondingly, an indicator of X and indicators of Z, x and z are externally consistent whether the association among x and z is the same as the three correlations: x with its construct X, z with its construct Z, and X with Z. Therefore, if X is internally and externally consistent, it will be unidimensional. External consistency is recommended by items that "cluster together in a matrix of sorted or ordered similarity coefficients" (Anderson and Gerbing 1982, p. 458). According to Gerbing and Anderson (1988) there is a little practical difference between the coefficient alpha (α) and latent variable reliability (ρ) for sufficiently unidimensional constructs, the coefficient alpha could be employed to preliminarily assess reliability.

Composite reliability assessment

CFA allows the computation of an additional estimation of a composite reliability, namely a construct's reliability (Gerbing and Anderson 1988, Hair *et al.* 2010). Composite reliability is a measure of reliability and assesses the internal consistency of the measured variables indicating a latent construct (Hair *et al.* 2010). According to Hair *et al.* (2010), composite reliability is a principal measure used in evaluating the overall reliability of the measurement model, for every latent construct in it. Hair *et al.* (2010) note that the minimum value for composite reliability should be 0.7, which indicates that the measures all represent the same latent construct consistently (Nunnally and Bernstain 1994). Construct reliability (Cronbach-alpha) measures the indicators' unidimensionality (inter-correlation) with their latent constructs (Hair *et al.* 2010).

Average variance extracted (AVE) assessment

The average variance extracted (AVE) is a measure of the common variance in a latent variable (LV), that is, the amount of variance that is captured by the latent variable in relation to the variance due to random measurement error (Dillon and Goldstein 1984; Fornell and Larker 1981). In different terms, AVE is a measure of the error-free variance of a set of items. According to Fornell and Larker (1981), AVE represents a stronger indicator of the construct reliability than the composite reliability. The average variance extracted (AVE) measures the overall amount of variance captured by the indicators relative to measurement error, and it should be equal to or exceed 0.50 to justify using a construct and ensure the validity of the scale under investigation (Hair *et al.* 2010). Fornell and Larcker (1981) state, "if it is less than 0.50, the variance due to measurement error is larger than the variance captured by the construct, and the validity of the construct is questionable" (p. 46).

Nomological validity

In theory development and testing, to achieve construct validity, nomological validity is an essential step (Bagozzi 1980, Gerbing and Anderson 1988, Nunnally 1978, Steenkamp and Trijp 1991). According to Peter (1981) and Peter and Churchill (1986), nomological validity is used to test hypothesised relationships among different constructs and the empirical relationship between measures of different constructs. Nomological validity refers to the expected behaviour of the measure and examines whether constructs behave as expected in theoretical and empirical terms (Peter and Churchill 1986). The goodness-of-fit indices are used to test the nomological validity of the measurement models (Steenkamp and Trijp 1991).

Convergent validity
Convergent validity refers to the homogeneity of the construct and is the extent to which independent measures of the same construct converge or are positively correlated (Gerbing and Anderson 1993, Malhotra and Birks 2000, Peter and Churchill 1986) with other measures of the same construct. Convergent validity may be assessed on the basis of construct reliabilities (Anderson and Gerbing 1988). Convergent validity is related to the internal consistent validity between each construct item, i.e. high or low correlations, and is shown by item reliability, composite reliability, and average variance extracted (Fornell and Larcker 1981). Convergent validity assesses the t-values and level of significance of the factor (Chau 1997). High inter-item correlations within each construct indicate convergent validity (Chau 1997; Shiu *et al.* 2009). Nunnally (1978) suggests that a 0.7 or higher reliability implies convergent validity, while measures with reliabilities above 0.85 include more than a 50% error variance.

Discriminant validity
Discriminant validity is defined as whether measures of one construct are not highly correlated with measures of others (Chau 1997, Malhotra and Birks 2000, Peter and Churchill 1986) i.e. when there is a negative correlation between the experiment's measure and the measurement of different constructs (Shiu *et al.* 2009). Since the association between two constructs is significantly lower than 1.00, the presence of discriminant validity is indicated (Anderson and Gerbing 1988; Bagozzi *et al.* 1991). Discriminant validity can be assessed for two estimated constructs by constraining the estimated correlation parameter (φij) between them to 1.00 and then performing a chi-squared difference test on the values obtained for the constrained and unconstrained model" (Anderson and Gerbing 1988, p. 416). Foroudi (2019) suggests that where the restricted model shows a poorer fit than the unrestricted model, there is evidence of discriminant validity. Discriminant validity can be measured by the AVE for each construct and compared with the square correlation between them (Fornell and Larker 1981). If the squared correlation (error-disattenuated or structural equation model) between two LVs is less than either of their individual AVEs, this suggested the constructs each have more error free (extracted or internal) variance than variance shared with other constructs (r2). Furthermore, they are more internally correlated than they are with other constructs and this suggests the discriminant validity of the target variance extracted (Fornell and Larker 1981).

Validity - summary
In summary, establishing validity is an essential part of the research process (Garver and Mentzer 1999) and should signify the unidimensionality of a construct (Steenkamp and Trijp 1991), reliability, nomological validity, convergent validity, and discriminant validity (Peter 1981; Steenkamp and Trijp 1991), for the research to use structural model evaluation.

Ethical considerations
Academic research needs to be aware of the ethics behind the research activity. These are based on the guidelines provided by the University ethics form and the British Educational Research Association (2004). All business and social researchers share a number of ethical concerns (Jowell 1986). Researchers must conduct their research following these basic rules:

- Protect the statutory rights of respondents by avoiding unnecessary interruption, obtaining permission and protecting privacy;
- Outline the research questions objectively;
- Be aware of social and cultural differences;
- Give full information on the methodologies to respondents;
- Clarify all details of the research in correspondence or communications with respondents;
- Record all interviews and focus groups sessions unless one of the participants disagrees

Case study - HSBC: Consumers' perception towards visual identity
This case study research was designed to identify the factors that influence how consumers perceive a corporate logo (in this case that of the bank, HSBC) and how this in turn influences their perception of corporate image and corporate reputation. It shows that the main factors that influence perceptions of the corporate logo are corporate name, design, and typeface, and that the logo does influence the consumer's perception of corporate image, their attitude to advertisements, their familiarity with the brand, their recognition of it and their perception of corporate reputation.
H1: The more favourably the corporate name is perceived by consumers, the more favourable the attitude consumers have towards the corporate logo.
H2: The more favourably the corporate typeface is perceived by consumers, the more favourable the attitude of the consumers towards the corporate logo.
H3: The more favourably the design of a company's logo is perceived by consumers, the more
H4: The more favourably the colour used in a company's logo is perceived by consumers, the more favourable the attitude consumers have towards the corporate logo.
H5: The more favourably the corporate logo of an organization is perceived by the consumers, the more favourable the image consumers have towards the company.
H6: The more favourable the image consumers have towards the company's corporate image, the more favourable the company's reputation is perceived by consumers.
H7: The more favourably the corporate logo of an organization is perceived by consumers, the more favourable will be their attitude towards that corporate advertisements.
H8: The more favourable the consumers' attitude towards a company's advertisements, the more favourable will be their image of the company.
H9: The more favourably the corporate logo of an organization is perceived by consumers, the more consumers feel familiar with the product or the company.
H10: The more consumers feel familiar with the company or product, the more favourable the image consumers have towards the company.
H11: The more favourably the corporate logo of an organization is perceived by consumers, the greater the impact on the product and company recognizability.
H12: The more that consumers recognize the company or the product, the more favourable the image consumers have towards the company.

The relationship between the hypotheses in the model is shown in Figure 5.3.

(Take in Figure 5.3. here)

Data Collection
The sample was drawn from consumers of the Hong Kong and Shanghai Banking Corporation (HSBC) within the United Kingdom. 1,352 self-administered questionnaires were distributed in London, using convenience sampling. 332 usable completed questionnaires were received. Prior to this survey, seven interviews were conducted with communication and design consultants and four focus groups were carried out with marketing lecturers and MBA students. The researchers created a large pool of items for each of the constructs based on literature review and qualitative data and the focus group and interview included in this study. The construct items were examined for appropriateness and clarity of wording by seven faculty members in the researchers' department of marketing who were familiar with the topic, as well as five marketing managers and consultants, and the items were assessed for content validity by using judging procedures The participating faculty members, marketing managers and consultants were also asked to comment on whether the questionnaire appeared to measure the intended construct, if any ambiguity or other difficulty was experienced in responding to the items, as well as asking for any suggestions they deemed suitable. Based on this, some items were eliminated, and others modified. The modified questionnaire was critically examined by seven academic experts in respect of domain representativeness, item

specificity, and construct clarity. Minor refinements were then made to improve the question specificity and precision, and some questions were eliminated. This was followed by another phase of pre-tests , to check that the measurement instrument clearly generated reliable and valid measures (Saunders et al., 2007). The questionnaire was completed in the pre-test by 50 academics (lecturers and doctoral researchers); the pre-test respondents were not invited to participate in the final study because it may have impacted on their behavior if they had already been involved in the pilot (Exploratory factor analysis (EFA) was performed in the pilot study to reduce the items and identify any pattern in the data (De Vaus, 2002). The scale showed a high degree of reliability. Some items were eliminated due to low reliability.

Analysis and Results

The research conceptual framework was tested by employing two-stage structural equation modelling (SEM). First, multi-item measures were purified examined psychometric properties were examined by performing confirmatory factor analysis (CFA) to assess the measurement properties of the existing scales' validity. The initial CFA confirmed that the absolute correlation between the construct and its measuring of manifest items (i.e., factor loading) was above the minimum threshold criteria of .7 and satisfied the reliability requirements. The Cronbach's α was higher than the required value and satisfied the requirements of the psychometric reliability test. The goodness of fit indices of model modification suggested an acceptable fit for the model: The measurement model was nomologically valid and each criterion of fit thus indicated that the proposed measurement model's fit was acceptable. Therefore, the model fit was adequate (Hair et al., 2006). The model's internal structure was examined by testing the discriminant validity, while the homogeneity of the construct was also tested by convergent validity. Two reliability measures for each construct were examined: composite reliability and average variance extracted. These measures satisfied the recommended reliability criteria (Hair et al., 2006). The assumed causal and covariance linear relationship among the exogenous (independent) and endogenous (dependent) latent variables were estimated. Based on the structural model, the research hypotheses were examined suing the standardized estimate and t-value (critical ratio). Goodness-of-fit indices of model modification provided mixed evidence about model fit.

Hypothesis testing

Given the directional nature of the research hypothesis, the importance tests conducted were all one-tailed. With regard to the antecedents of corporate logo, the strong support for three of the four hypotheses were found. With regard to corporate name, it was found that the more favourably the corporate name is perceived by consumers, the more favourable is their attitude towards the corporate logo, which supports H1. The outcome is similar with H2, which proposes that the more favourably the corporate typeface is perceived by consumers, the more favourable is their attitude towards the corporate logo. With regard to design, there was strong support for hypothesis H3: the more favourably the design of a company's logo is perceived by consumers, the more favourable is their attitude towards the corporate logo. However, an unexpected result shows that the relationship between colour and corporate logo evaluation was non-significant, and the regression path unexpectedly illustrated a negative relationship between these two variables. Therefore, hypothesis H4 was rejected because the results were not statistically significant.

Concerning the consequences of corporate logo, there was strong support for five out of eight hypotheses. H5 is supported: the more favourably the corporate logo of an organization is perceived by consumers, then the image consumers have of the company is more favourable. H6 was supported: the more favourably that consumers perceive a company's corporate image, then the company reputation is perceived more favourably by them. There iwas a strong relationship between the evaluation of corporate logo from consumers' perspective towards an organization's advertisements (H7), familiarity (H9), and recognizability (H11). Consumer's attitude towards advertisements, familiarity, and recognizability mediated between corporate logo and corporate image (which is in line with the qualitative study and theoretical expectation). However, the relationships between a) the consumer's attitude towards the advertisements and corporate image, b) familiarity and corporate image, and c) recognizability and corporate image were not significant, so hypotheses H8, H10 and H12 were rejected and these relationships were excluded from the model. The results implied that recognizability, attitude towards the advertisements, and familiarity do not mediate mediator between corporate logo and corporate image and did not have a significant impact on corporate image. Therefore, hypotheses H8, H10 and H12 were regarded as rejected and those relationships were excluded from the model.

Issues for further discussion

Further research opportunities could concern a broader analysis of the analysed case. Interdisciplinary issues could also provide relevant insights, particularly in terms of research methods. Future inquiries could be directed towards recognising the research design suitable for carrying out this marketing research study for HSBC, providing a rationale for it; deciding which research method could be used for data collection, explaining the selection of the administrated data collection tool (focusing on the reason for choosing the tool and on the pros and cons associated with the chosen method of administration).

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