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EDITORIAL PERSPECTIVE

Research Methods in a Nutshell: What, Why, When, Where, Who, and How?

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ABSTRACT

Over the years, it has been observed that discussions on research methods in academic writing often oscillate between two extremes: either abstract philosophical debates or purely technical instructions. Many early career researchers—and sometimes even experienced scholars—struggle with the simple question: *Which method should be used?* The answer, however, is rarely straightforward. It depends not only on the convenience or the disciplinary habit of a researcher but also on the nature of the research question, the timing of the inquiry, the context in which it is situated, the units of analysis involved, and the resources available for its execution. Textbooks have contributed richly to our understanding, yet they frequently overwhelm rather than provide clarity. In this context, we provide a comparative overview of important research methods using the 5WH framework (What, Why, When, Where, Who, and How), based on years of experience as an Editor. We provide a synthesis of regression-based methods, experimental methods, multivariate methods, qualitative methods, mixed methods, configurational and comparative methods (QCA family), big data and computational methods, AI-driven methods and techniques, and finally, literature review methods.

1 | Introduction

Textbooks cover research methods comprehensively but often do not provide a comparative logic that assists researchers in making informed choices. A recurring concern amongst researchers is the misalignment between the research problem posed and the method adopted (Paul 2025). This mismatch can weaken the promising contributions that a study intends to offer. To address this, we present an editorial perspective that is straightforward in structure and also helps in choosing the best possible method. The 5WH framework—What, Why, When, Where, Who, and How (Paul 2024)—offers such a heuristic by providing a comparative map for method selection and justification.

Applied to research methods, each 'W' illuminates a vital dimension: What directs the nature of the inquiry and the construct under examination; Why relates to the purpose, theoretical justification, or practical relevance; When and Where to the temporal and contextual setting; Who identifies the respondents, participants, or units of analysis; and How explains the tools, frameworks, or procedures employed. The 5WH framework helps in simplifying comparative reasoning (Paul and Barari 2022).

A doctoral student or supervisor designing a study, a reviewer or associate editors evaluating a manuscript, or a practitioner applying a method can all benefit from this article: Have thresholds

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been met adequately?. This editorial perspective, therefore, proposes the 5WH framework as a compact but rigorous guide to method selection. It provides a compass, a means of aligning the method with the question, context, and purpose. In doing so, it seeks to bring clarity where there is often confusion, and to foster better alignment between methodological choices and the research problems they are intended to address.

Using the 5WH framework (Paul, Khatri, and Kaur Duggal 2023), we outline the diversity of methodological approaches available to researchers. Research has never been confined to a single pathway; rather, it has evolved into a broad spectrum of designs and techniques. For clarity and ease of navigation, these approaches can be classified into different families. Quantitative methods provide tools for measurement, prediction, and hypothesis testing (Paul 2024). Qualitative methods illuminate meaning, context, and lived experience (Paul 2025). Mixed methods deliberately integrate the two, enabling both breadth and depth. Big data and computational approaches extend inquiry into digital traces, large-scale analytics, and high-dimensional modelling. Finally, AI-driven methods and techniques have emerged as a transformative frontier, enabling generative, predictive, and adaptive forms of research that redefine how data can be gathered and analysed (Sharma et al. 2025).

Presenting methods within such a classification not only offers structure but also allows readers to appreciate their complementarities and distinctions. The intent is not to privilege one family over another, but to provide a consolidated view that highlights the choices available, and to prepare the ground for later discussion of how researchers can evaluate the merits of these methods and choose the right approach.

2 | Regression-Based Methods

2.1 | What

Regression methods are employed in behavioural, time series data, and cross-sectional data. Researchers using survey data in consumer research usually examine the impact of independent variables (such as advertising spend, customer satisfaction, or digital engagement) on dependent outcomes (such as sales, purchase intention, or loyalty) (refer to Figure 1). They answer what type of relationship exists between predictors and outcomes and whether that relationship is significant and meaningful (Baber et al. 2020; Kaurav et al. 2015). In accounting, finance, and economics, (except behavioural side) researchers often employ distinct regression approaches compared with those commonly used in consumer and marketing research (Demydyuk and Carlbäck 2023). They frequently rely on advanced time-series models such as vector autoregression (VAR), GARCH, and ARCH, complemented by robustness diagnostics like multicollinearity, autocorrelation, and heteroscedasticity checks (for thresholds, refer Table 1). Analyses proceed only when these assumptions are met (Kumar et al. 2025).

- Linear regression: assesses how continuous predictors (e.g., perceived quality, price) influence a continuous outcome (e.g., repurchase intention).
- Logistic regression: models binary outcomes (e.g., purchase vs. no purchase, churn vs. retention).
- Hierarchical/multilevel regression: accounts for nested structures in marketing data (e.g., consumers within regions, stores within chains, or customers across time points in panel studies).

2.2 | Why

The rationale for regression in business research, particularly in consumer research and behavioural studies, is its ability to quantify effects and inform managerial decisions (Mishra et al. 2022). For example:

- Does customer satisfaction predict loyalty scores? (linear regression)
- What factors increase the probability of adopting a new retail technology? (logistic regression)
- How do store-level promotions interact with regional demographics in shaping sales outcomes? (multilevel regression)

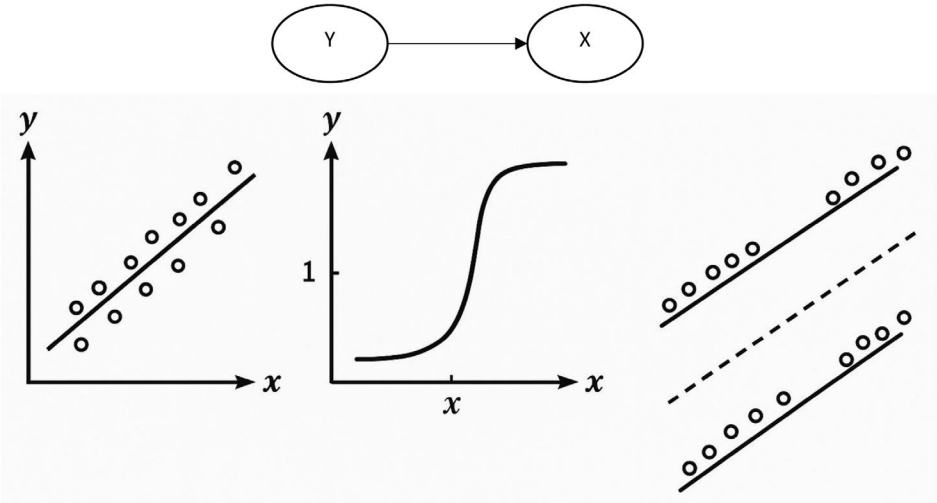


FIGURE 1 | Basic regression portraying the relationship between a predictor variable (Y) and an outcome variable (X), linear, logistic, and multilevel regression. (*Source:* Authors).

TABLE 1 | Thresholds of adequacy for regression-based methods in marketing research.

Method	Key thresholds	Use cases for marketing research
Linear regression	Sample size: $N \geq 50 + 8k$ (k = predictors) Adjusted R^2 (context-specific, but > 0.20 often acceptable in consumer research) Multicollinearity: VIF < 10 Residuals: normality & homoscedasticity checks	Often applied in survey-based models (e.g., satisfaction → loyalty). Low R^2 may still be meaningful in consumer behaviour research due to complex influences.
Logistic regression	≥ 10 events per predictor variable (EPV) Classification accuracy > 70% desirable Pseudo R^2 (Nagelkerke $R^2 \geq 0.20$ as moderate) Hosmer–Lemeshow test: non-significant ($p > 0.05$)	Used in adoption/churn studies (e.g., adoption of mobile payments). Interpretation often focuses on odds ratios rather than R^2 alone.
Multilevel/ hierarchical regression (HLM)	≥ 20 groups recommended (with 20+ observations per group) ICC (intraclass correlation coefficient) > 0.05 justifies multilevel model Group-level variance significant ($p < 0.05$) Sufficient level-2 sample sizes (e.g., ≥ 30 stores in retail studies)	Applied when consumers are nested within stores, or sales reps within teams. Essential for retailing and service management research.

Source: Authors.

2.3 | When

Regression is most suitable when relationships amongst variables are hypothesised, and data are collected in measurable form (survey responses, experimental manipulations, or secondary data). Researchers typically use regression in:

- Survey-based studies (e.g., linking attitudes to behavioural intentions).
- Experimental studies (e.g., testing how different ad appeals influence purchase intention).
- Panel or customer-level datasets (e.g., modelling store loyalty across locations).
- Time series data with daily, weekly, or monthly frequency.

2.4 | Where

Applications of regression are diverse across the social sciences and business disciplines:

- In psychology and sociology, regression is applied to examine relationships between attitudes, social influences, and behaviours.
- In education research, it is used to analyse predictors of learning outcomes and student performance.
- In consumer and behavioural research, linear regression is applied to test attitude–intention–behaviour models.
- In digital marketing, logistic regression is used to predict click-throughs or conversions from online ads.
- In retailing research, multilevel regression is applied when sales data are clustered by store or geography.
- In organisational studies (HR/OB), regression helps assess the effects of workplace policies on satisfaction, loyalty, and retention.

2.5 | Who

The unit of analysis depends on the study:

- Individual-level: consumers, online users or survey respondents.
- Group-level: retail outlets, sales teams, or product categories.
- Hierarchical: customers nested within segments, or transactions within customers.

2.6 | How

Regression is normally employed using estimation procedures such as ordinary least squares (OLS) for linear regression or maximum likelihood for logistic regression. For example, Baber et al. (2020) evaluated the impact of individual market orientation (IMO) on selling and customer orientation for insurance agents. Adequacy is assessed through both statistical thresholds and substantive interpretation:

Linear regression formula

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \ \ldots \ + \beta kXk + \epsilon$$

Example: Purchase intention $= \beta_0 + \beta_1$ (Brand Trust) $+ \beta_2$ (Price Perception) $+ \varepsilon$.

Logistic regression formula

$$\text{logit}(p) = \ln\left(\frac{p}{1-p}\right) = \beta 0 + \beta 1X1 + \ \ldots \ + \beta kXk$$

Example: Probability of adoption of mobile payment $= \beta_0 + \beta_1$ (Perceived Usefulness) $+ \beta_2$ (Social Influence).

Hierarchical regression

$$Yij = \beta 0 + \beta 1Xij + uj + \epsilon ij$$

where observations (i) are nested in groups (j), e.g., customers within stores.

Example: Customer satisfaction at store level $= \beta_0 + \beta_1$ (Individual Perceived Value) $+ u$(Store) $+ \varepsilon$.

Regression models are implemented using widely available statistical software. Traditional packages such as SPSS and Stata remain popular for their user-friendly interfaces and robust regression modules. Open-source platforms such as JAMOVI, R (packages: lm, glm, lme4), and Python (libraries: statsmodels, scikit-learn) provide greater flexibility and reproducibility. For advanced applications such as hierarchical models or survival analysis, Mplus and HLM software are often used. Commercial solutions like EViews are also common in time-series contexts (Kaurav et al. 2021; Zheng 2023) (refer Table 1).

2.7 | Common Misuses of Regression

- Treating correlation as causation without experimental or longitudinal design.
- Ignoring key assumptions (linearity, homoscedasticity, independence).
- Overfitting with too many predictors in small samples.
- Using R^2 inflation as proof of model strength without diagnostics.

2.8 | Guidelines for Authors

Regression is not simply a statistical tool; it is a decision compass. It allows scholars to test models of consumer behaviour, evaluate campaign effectiveness, and predict market outcomes. However, thresholds must be respected; an impressive R^2 without diagnostic checks is meaningless, and significant coefficients without conceptual clarity are misleading. Properly aligned, regression provides scholars with both explanatory and predictive power, making it one of the most enduring tools in the methodological repertoire. When misapplied, regression can produce fragile insights. However, once aligned with theory and thresholds, it is bound to be a powerful tool for both explanation and prediction.

3 | Experimental Research Methods

3.1 | What

Experimental research is used to establish causal relationships by manipulating independent variables and observing their effects on dependent outcomes under controlled conditions. It answers what happens when a specific factor is changed (Roy et al. 2025) (see Figure 2).

In multivariate research, constructs are abstract concepts (e.g., trust), measured via variables (survey questions), items (individual indicators), and aggregated into factors (latent dimensions). This distinction clarifies the progression from conceptualisation to measurement and analysis and helps researchers see how observed responses are systematically linked to underlying theoretical ideas. For instance, the construct of Brand Trust may be measured through a variable such as 'perceived reliability,' which is operationalised as survey items like 'This brand delivers on its promises.' These items, when analysed together, load onto a factor representing the latent dimension of brand reliability.

Following this measurement logic, researchers often test their hypotheses through experimental designs. The following are some of the popular types of experiments used in marketing and consumer research:

- Lab experiments: conducted in controlled environments to test cause–and–effect (e.g., exposure to different ad appeals).
- Field experiments: conducted in real-world settings, often with customers or stores (e.g., A/B testing of online promotions, in-store signage).
- Quasi-experiments: lack random assignment but still involve intervention (e.g., pre–post studies in a retail chain).

3.2 | Why

The purpose of experiments is to move beyond correlation and demonstrate causation. In marketing research, experiments help answer:

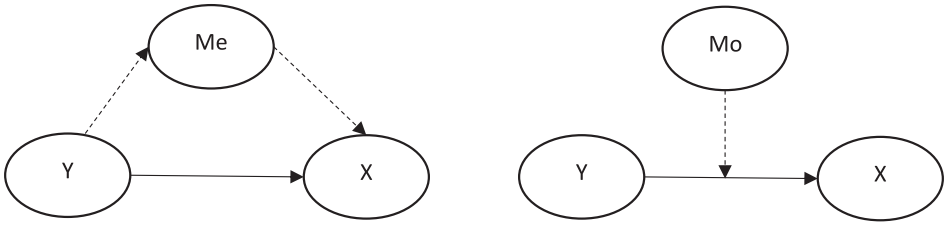


FIGURE 2 | Mediation and moderation framework showing how variable Me/Mo transmits the effect of predictor Y onto outcome X. (*Source:* Authors).

TABLE 2 | Thresholds of adequacy for experimental research designs.

Type of experiment	Key thresholds	Use cases for marketing research
Lab experiments	Random assignment required; sample size: power ≥ 0.80 (often ~30–50 per condition)	Useful for testing ad framing, sensory perceptions; may lack realism.
Field experiments	Natural setting, treatment vs. control groups; sufficient clusters (≥ 20 stores/regions)	Strong ecological validity; used in retailing and service management.
Quasi-experiments	Pre–post measures, matched groups; statistical controls (ANCOVA, propensity scores)	Applied when randomisation is not feasible, e.g., new product launches.

Note: Kumar et al. (2025).
Source: Authors.

- Does emotional appeal in advertising increase purchase intention compared to rational appeal?
- Do price discounts increase footfall more than loyalty rewards?
- Will algorithm-driven product recommendations outperform human-curated ones?

3.3 | When

Experiments are most suitable when researchers need strong evidence of causal relationships. They are widely used in:

- Consumer behaviour studies (e.g., testing message framing effects).
- Digital marketing (e.g., A/B testing of website layouts, email subject lines).
- Retailing (e.g., testing shelf placement or dynamic pricing interventions).

3.4 | Where

- Lab settings: allow control over extraneous variables, but risk artificiality.
- Field settings: offer ecological validity but reduced control.
- Online platforms: increasingly used for behavioural experiments (Amazon MTurk, Prolific, Qualtrics panels).

3.5 | Who

Units of analysis vary by context:

- Individual consumers (lab-based product trials).
- Customer groups (loyalty programme experiments).
- Stores/regions (field trials of pricing, assortment, or promotions).

3.6 | How

Experiments are executed through controlled manipulation of variables:

- Randomisation ensures comparability between groups.
- Manipulation checks confirm that participants perceived the intervention as intended.
- Outcomes are analysed with *t*-tests, ANOVA, or regression models.

Formula (simple experimental model):

$$Y = \mu + \tau i + \epsilon$$

where Y is the outcome, μ is the grand mean, τi is the treatment effect, ϵ is the error.

Example: Testing whether personalised product recommendations (T1) increase conversion rates compared to generic recommendations (T0).

Experiments are often designed and deployed using Qualtrics, SurveyMonkey, and Gorilla Experiment Builder (for behavioural tasks). Cognitive psychology software such as PsychoPy and E-Prime is used for controlled laboratory experiments, whilst platforms such as MTurk, Prolific, and CloudResearch facilitate online subject recruitment. Statistical analysis of experimental data can be conducted in SPSS (ANOVA modules, GLM family), R (afex, lme4), or Jamovi, ensuring that randomisation and power thresholds are verified. PROCESS macro by Prof. Andrew F. Hayes is a popular tool for mediation, moderation, and continuous process analysis (Hayes 2018; Hayes 2022; Hayes and Rockwood 2020; Igartua and Hayes 2021; Aruldoss et al. 2023) (for thresholds, see Table 2).

3.7 | Common Misuses of Experiments

- Over-reliance on student samples, limiting external validity.
- Manipulation without adequate checks.
- Ignoring ethical issues in field experiments (e.g., deceptive pricing).
- Treating small-sample lab findings as generalisable to large markets.

3.8 | Guidelines for Authors

Experiments are the gold standard for causal inference in marketing, but their strength depends on alignment between design

and research question. Misapplied experiments risk producing elegant but irrelevant findings; well-designed studies, by contrast, provide clarity that few other methods can match. For more information on experimental design-based research, refer to Stoner et al. (2023).

4 | Multivariate Methods

4.1 | What

Multivariate methods examine relationships amongst multiple variables simultaneously, often to uncover or validate latent constructs that cannot be measured directly. EFA (Exploratory Factor Analysis) identifies latent dimensions underlying observed variables (e.g., brand trust scale) (Chowdhary et al. 2020) (see Figure 3 for categories).

- CFA (Confirmatory Factor Analysis): Tests hypothesised measurement models of constructs (e.g., satisfaction → loyalty framework) (Dash and Paul 2021; Kaurav, Kainthola, et al. 2024).
- SEM (Structural Equation Modelling): Integrates measurement and structural models to test complex causal relationships (e.g., satisfaction → trust → loyalty). There are two possible techniques of SEM—1. CB-SEM (Covariance-based SEM) (Dash et al. 2021; Mehra et al. 2021) and 2. PLS-SEM (Partial Least Squares-based SEM) (Dul 2024; Ramtiyal et al. 2025; Saxena et al. 2025; Srivastava et al. 2024). We suggest readers to refer Dash and Paul et al. (2021), titled CB-SEM versus PLS-SEM, for research in the social sciences.
- NCA (Necessary Condition Analysis): Identifies conditions that are necessary but not sufficient for an outcome to occur (e.g., a minimum level of brand trust required for loyalty). NCA is often used alongside SEM, adding a complementary logic by detecting bottleneck thresholds that traditional sufficiency-based models cannot capture (Han, Baah, et al. 2025; Tiwari et al. 2024).

4.2 | Why

The main reasons why multivariate methods are used are because they help:

- Ensure constructs are reliable and valid (For example, attitudes, perceptions, intentions)
- Permit testing of mediators and moderators.
- Allow comparison across groups (e.g., cross-cultural consumer studies).

Examples:

- EFA: Uncovering underlying factors in 'customer experience' surveys.
- CFA: Testing whether 'service quality' is represented by responsiveness, empathy, and assurance.
- SEM: Examining how 'customer engagement' influences 'brand advocacy' through 'trust.'
- CFA: 'Minimum digital literacy' as a prerequisite for adopting 'mobile payment technologies.'

4.3 | When

These methods are used when the research question involves latent constructs or multiple interrelated variables.

- EFA: early stages of scale development or exploratory work.
- CFA: once a measurement structure is hypothesised.
- SEM: when theory predicts paths amongst latent constructs.
- NCA: When theory or observation suggests that outcomes require minimum conditions rather than being gradually built by predictors. It is particularly valuable in- Adoption studies, Retailing and CRM (minimum frequency of engagement before loyalty).

4.4 | Where

Multivariate methods are applied widely in marketing research:

- Consumer behaviour: validating scales (e.g., perceived value, involvement), identifying thresholds of trust, involvement, or engagement.
- Services marketing: testing SERVQUAL dimensions.
- Retailing/Customer Relationship Management (CRM): linking satisfaction, loyalty, and retention.
- Cross-national research: testing measurement invariance across countries.
- Digital marketing: Determining the minimum online presence required for influencer credibility.

4.5 | Who

The unit of analysis is usually the individual respondent (survey-based), but data may also come from store-level metrics or panels. Sample size adequacy is critical, which includes:

- EFA: minimum $N \geq 5$–10 respondents per item.
- CFA/SEM: $N \geq 200$ is often recommended for stable solutions.
- NCA: Individual-level: consumers, employees, or respondents in survey data, $N \geq 200$ recommended for stability

4.6 | How

- EFA: Principal Component or Principal Axis Factoring with rotation (Varimax/Oblimin).

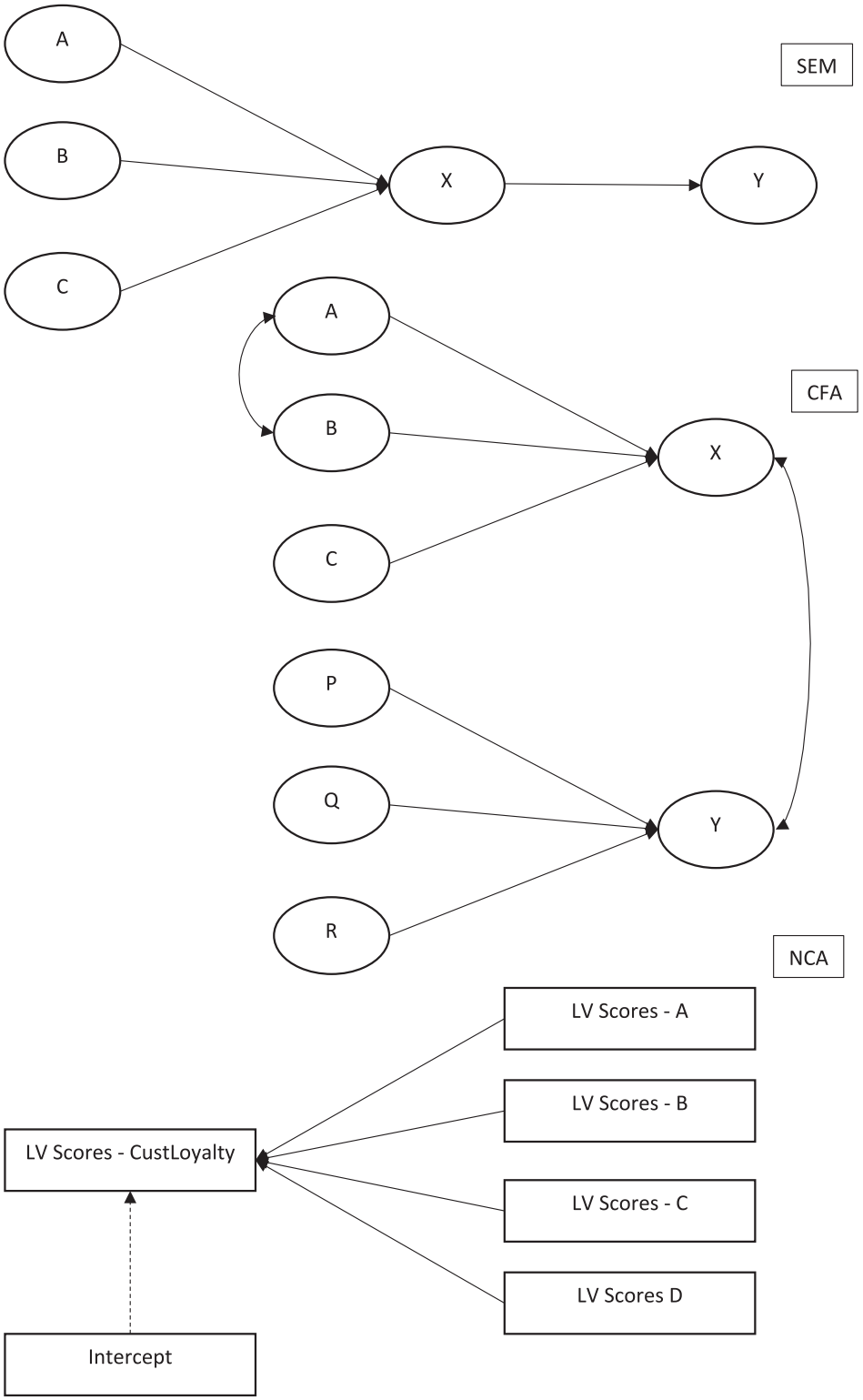


FIGURE 3 | Models of multivariate analysis: Structural equation modelling (SEM), confirmatory factor analysis (CFA), necessary condition analysis (NCA), and LV Score, latent variable score. (*Source:* Authors).

- CFA: Maximum likelihood estimation of measurement models.
- SEM: Combines CFA with structural paths, estimated via covariance-based SEM (theory-driven) or PLS-SEM (prediction-driven).
- NCA: The whole process involves—Plotting independent variable (condition) against dependent variable (outcome); Identifying the ceiling line (upper-left empty space); Calculating effect size *d* to assess necessity strength; Producing a bottleneck table showing required minimum levels.

Formulas:

EFA/CFA (measurement model):

$$X = \Lambda\xi + \delta$$

where X is the observed indicators, Λ is the loadings, ξ is the latent constructs, δ is the uniqueness or specific error variance associated with a particular observed variable.

SEM (structural model):

$$\eta = B\eta + \Gamma\xi + \zeta$$

where η is the endogenous constructs, ξ is the exogenous constructs, B, Γ is the path coefficients.

Example: Customer Satisfaction (latent) → Loyalty (latent), mediated by Trust (latent).

NCA:

$$d = \frac{CE}{T}$$

where CE is the ceiling zone (space above the ceiling line), T is the total empirical data space.

Exploratory factor analyses are commonly conducted using SPSS. AMOS, SmartPLS, ADANCO, LISREL, Mplus, and Stata are widely used for confirmatory factor analyses. Open-source alternatives include R (psych, lavaan, semTools) and Jamovi (SEMLj plugin). For SEM specifically, AMOS, Mplus, EQS, and LISREL dominate theory-driven applications, whilst SmartPLS, WarpPLS, and ADANCO are widely used for prediction-oriented PLS-SEM. NCA is supported in R (NCA package) and in SmartPLS, enabling easy integration with SEM analyses (Rana et al. 2023). Refer Table 3 for thresholds values, Table 4 for differentiating CB-SEM and PLS-SEM and Table 5 to understand should you extend to NCA, when it is suitable.

4.7 | Common Misuses of Multivariate Methods

- Performing EFA on small samples with unstable factors.
- Using CFA/SEM with poor model fit but still 'accepting' results.
- Ignoring discriminant validity and reporting overlapping constructs.
- Treating PLS-SEM (predictive) as equivalent to CB-SEM (theory testing).
- Treating necessary conditions as sufficient (ignoring that other factors still matter).
- Using NCA on very small samples leads to unstable ceiling lines.
- Misinterpreting weak necessity ($d < 0.1$) as meaningful.

4.8 | Guidelines for Authors

Multivariate methods are the most dependable and frequently used tools in behavioural research, where latent constructs dominate. Their strength lies in rigor, but they are also prone to misuse when thresholds are ignored, or models are fitted without theoretical clarity. Properly applied, they transform abstract concepts into measurable, testable structures that advance both theory and practise.

CB-SEM and PLS-SEM are not substitutes but complements. CB-SEM excels in theory testing with strong models, whilst PLS-SEM is advantageous for prediction and exploration in emerging areas. The choice should be driven by the research question, data conditions, and purpose—not by software convenience.

NCA shifts attention from 'drivers' to 'prerequisites.' In marketing, this perspective reveals bottlenecks that managers must cross before other strategies can work. whilst it complements regression and SEM, it should not replace them; necessity is one piece of the causal puzzle.

5 | Qualitative Methods

5.1 | What

Qualitative methods are designed to capture meanings, processes, and contexts that are often overlooked by quantitative measures. In social sciences, focusing on behavioural research, they help answer what lies behind consumer perceptions, organisational practises, and cultural patterns.

- Case study (single- or multiple-case): Examines a bounded system (e.g., a retail chain, a start-up ecosystem) in depth. Integrating the tenets of a theoretical framework in the context of a case study is important. Researchers are suggested to refer to Paul and Sahadev (2018) to learn how to do this.
- Ethnography: Immersive exploration of consumer or organisational culture (e.g., studying digital/online fan communities via netnography) (Sima et al. 2025).
- Phenomenology: Focuses on lived experiences of individuals (e.g., how consumers experience luxury or sustainability) (Bhalla et al. 2025).
- Grounded theory: Builds theory inductively from data (e.g., developing a model of consumer trust in AI systems) (Chawla et al. 2025; Demydyuk et al. 2024; Kainthola et al. 2024).
- Focus groups: Facilitated group discussions to surface shared opinions and language around products or campaigns.

5.2 | Why

- Qualitative methods address why consumers behave as they do by uncovering meanings, narratives, and symbolic processes.

TABLE 3 | Thresholds of adequacy for multivariate methods, including EFA, CFA, SEM, and NCA.

Method	Key thresholds	Notes for marketing research
EFA	KMO > 0.60	Used in scale development; exploratory studies of constructs like customer engagement.
	Bartlett's test significant ($p < 0.05$)	
	Factor loadings ≥ 0.40	
CFA	Factor loadings ≥ 0.50 (Preferably ≥ 0.60)	Applied in consumer surveys to validate measurement models (e.g., service quality).
	Cronbach's Alpha ≥ 0.70 (Acceptable), ≥ 0.80 (Good)	
	Composite reliability (CR) ≥ 0.70 (Acceptable)	
	Average variance extracted (AVE) ≥ 0.50 (Acceptable)	
	Chi-Square/degrees of freedom (χ^2/df) ≤ 5.0 (Acceptable), ≤ 3.0 (Good)	
	Goodness-of-fit index (GFI) ≥ 0.90 (Acceptable), ≥ 0.95 (Good)	
	Adjusted goodness-of-fit index (AGFI) ≥ 0.80 (Acceptable)	
	Comparative fit index (CFI) ≥ 0.90 (Acceptable), ≥ 0.95 (Good)	
	Tucker-Lewis index (TLI) ≥ 0.90 (Acceptable), ≥ 0.95 (Good)	
	Root mean square error of approximation (RMSEA) ≤ 0.08 (Acceptable), ≤ 0.06 (Good)	
	Standardised root mean square residual (SRMR) ≤ 0.08 (Acceptable), ≤ 0.05 (Good)	
	Discriminant validity: HTMT < 0.90	
SEM	CFA + $N \geq 200$ for stable estimation multi-group analysis requires measurement invariance tests	Common in marketing to test mediators (trust, satisfaction) and moderators (culture, demographics).
NCA	CFA + SEM + effect size (d): ≥ 0.1 (small), ≥ 0.3 (medium), ≥ 0.5 (large)	Indicates how much space is empty above the ceiling line.
	Ceiling line should be visually and statistically checked	Ensures necessary but not sufficient condition is present.
	Bottleneck table required for levels of condition for different levels of outcome	Helps identify managerial thresholds (e.g., minimum satisfaction score for loyalty).

Source: Compiled by Authors from multiple sources, some of the classical inspirations are Anderson and Gerbing (1988); Fornell and Larcker (1981); Bagozzi and Yi (1988).

- Case studies reveal complex causal chains and context-specific strategies (e.g., why certain retailers succeed in omnichannel adoption).
- Ethnography explains cultural consumption practises (e.g., why communities engage with brands as identity symbols).
- Phenomenology captures subjective meaning (e.g., why 'authenticity' matters to craft beer consumers).
- Grounded theory builds middle-range theories when existing frameworks are inadequate.
- Focus groups surface why target segments perceive products differently, providing insights for, i.e., campaign design.

5.3 | When

These methods are most suitable when the research is exploratory, theory-building, or context-dependent. For instance,

- Case studies and ethnography: when depth and context are essential.
- Phenomenology: when the researcher seeks to understand deep subjective experience.
- Grounded theory: when existing theory is insufficient.
- Focus groups: when preliminary insights are needed for survey or campaign design.

5.4 | Where

- Case studies: firms, markets, or industries (e.g., Tesla as a single-case on disruptive branding).
- Ethnography: cultural settings, physical or digital (e.g., in-store observation vs. netnography of online communities).
- Phenomenology: consumer interviews in natural settings.

TABLE 4 | Comparison of CB-SEM and PLS-SEM.

Aspect	CB-SEM (covariance-based SEM)	PLS-SEM (partial least squares SEM)
What it is	Theory-testing approach; estimates model fit based on covariance matrix.	Prediction-oriented approach; estimates model components using variance explained.
Primary aim	Confirmatory—tests whether data fit a hypothesised theory/model.	Exploratory & predictive—focuses on maximising explained variance (R^2, Q^2).
When to use	Strong theory exists	Theory is less developed or is exploration phase
	Hypotheses require confirmation	Focus is on prediction or exploration
	Model fit indices are critical	Models are complex or data quality is limited
Sample size	Preferred larger samples ($N \geq 200$ typical).	Smaller samples acceptable; rules of thumb: '10 times rule' ($10 \times$ max arrows pointing to construct).
Assumptions	Multivariate normality, continuous data, larger N.	More flexible: handles non-normal data, smaller N, formative indicators.
Evaluation criteria	Global fit indices: $\chi^2/df \leq 3$, RMSEA ≤ 0.08, CFI/TLI ≥ 0.90, SRMR ≤ 0.08.	Prediction-focused: R^2, Q^2, f^2 effect size, path coefficients, SRMR (recently adopted).
Strengths	Gold standard for theory testing	Suitable for exploratory & predictive aims
	Rich model fit diagnostics	Handles complex models with many constructs
	Supports mediation/moderation with rigour	Works with small to medium samples
Limitations	Sensitive to sample size & non-normality	Lacks established global fit indices
	Less suited for formative constructs	Sometimes misused as a substitute for weak theory
Marketing use cases	Validating well-established constructs (e.g., SERVQUAL, brand equity).	Exploring new constructs (e.g., customer engagement, digital trust) or predictive models (e.g., churn, adoption).

Note: Dash and Paul (2021).
Source: Authors.

TABLE 5 | Comparison of SEM and NCA.

Aspect	SEM (Structural equation modelling)	NCA (necessary condition analysis)
Logic	Tests sufficiency: Do predictors explain variance in outcomes?	Tests necessity: Is a minimum level of a predictor required for an outcome?
Purpose	Explains how much a factor contributes to outcomes.	Identifies bottlenecks that make outcomes possible or impossible.
Data Needs	Larger samples ($N \geq 200$ recommended).	Moderate samples ($N \geq 50$ sufficient for stable ceiling lines).
Output	Path coefficients, R^2, fit indices.	Effect size (d), ceiling line, bottleneck table.
Use Case	Testing theory, mediation, moderation, cross-group comparisons.	Detecting thresholds: e.g., minimum trust for loyalty, minimum awareness for adoption.
Complementarity	Shows strength and direction of relationships.	Reveals critical prerequisites that SEM may overlook.

Source: Developed based on the inputs from Han, Baah, et al. (2025).

- Grounded theory: iterative data collection in field contexts (e.g., start-up accelerators).
- Focus groups: neutral venues, online panels, or brand communities.

5.5 | Who

- Case studies: organisations, managers, policy-makers.
- Ethnography: communities, tribes, consumer collectives.

- Phenomenology: individuals sharing a lived experience (e.g., first-time luxury buyers).
- Grounded theory: diverse participants until saturation.
- Focus groups: carefully segmented participants (6–10 per group).

5.6 | How

- Case studies: triangulate interviews, archival data, and observation.
- Ethnography: prolonged immersion, thick description, reflexive notes.
- Phenomenology: in-depth interviews, analysis of lived narratives.
- Grounded theory: coding (open, axial, selective), constant comparison.
- Focus groups: guided discussion, content analysis, thematic coding.

Qualitative data collection and analysis are typically supported by software such as MAXQDA, NVivo (Aggarwal et al. 2023), ATLAS.ti, and Dedoose, which provide coding, categorisation, and theme development functions. Tools like Transana and f4transkript, Otter.ai support transcription and video analysis. For discourse or conversation analysis, specialist packages such as text-based Python libraries NLTK (i.e., Natural Language Toolkit), spaCy, Gensim, TextBlob, and Scikit-learn can be employed. Increasingly, these platforms integrate with AI-assisted coding modules, enabling semi-automated processing whilst preserving interpretive depth. In general, there is no simple and single way for achieving thresholds; still, refer to Table 6 for more details. The principle of saturation is followed for determining the sample size (Kainthola et al. 2024).

5.7 | Common Misuses of Qualitative Methods

- Treating anecdotal evidence as theory.
- Conducting shallow interviews/focus groups without saturation.
- Using case studies without triangulation.
- Over-generalising from context-specific insights.

5.8 | Guidelines for Authors

Qualitative methods bring voice, meaning, and depth to marketing research, complementing the statistical rigour of quantitative approaches. Their misuse often stems from treating them as 'quick fixes' rather than systematic designs. Applied rigorously, however, they uncover the cultural and experiential dimensions of marketing that numbers alone cannot capture. Authors are advised to refer to Crick (2021) for learning more about how to execute a classic qualitative study. Similarly, Paul and Sahadev (2018) show how to apply theoretical tenets in a case study context.

6 | Mixed Methods

6.1 | What

Mixed methods combine quantitative and qualitative approaches within a single study or research programme. They answer what happens when numerical breadth is complemented with interpretive depth.

- Sequential exploratory design (qual → quant): Qualitative findings guide survey design or scale development.
- Sequential explanatory design (quant → qual): Survey or experiment findings are followed by qualitative exploration to explain results.
- Concurrent triangulation: Both strands were collected in parallel and compared for convergence.
- Embedded design: One method nested inside another (e.g., interviews within a large-scale survey).

TABLE 6 | Thresholds of adequacy for qualitative research methods.

Method	Key thresholds	Use cases for marketing research
Case study	Multiple data sources (interviews, documents, observation). Triangulation essential.	Used for firm-level strategy or retail transformation research.
Ethnography	Prolonged engagement (months); field notes, observations, interviews.	Applied in consumer culture theory (CCT), digital ethnography in online brand communities.
Phenomenology	6–25 participants often sufficient; emphasis on depth not size.	Used to explore symbolic consumption (luxury, authenticity).
Grounded theory	Iterative coding; theoretical saturation (~20–30 interviews).	Useful for new domains (AI in marketing, sustainable practises).
Focus groups	3–5 groups, 6–10 participants per group; moderator neutrality.	Common in exploratory product testing, ad evaluation, segmentation studies.

Source: Authors.

- Multiphase design: Iterative cycles of quant and qual over time.

6.2 | Why

The rationale is that marketing phenomena are complex—attitudes, behaviours, and contexts often require both measurement and meaning. Mixed methods are used:

- To validate findings across methods (triangulation).
- To develop scales (qualitative → quantitative).
- To explain surprising results (quantitative → qualitative).
- To address multi-level problems (e.g., firm-level and consumer-level perspectives).

Examples:

- Using focus groups to generate items for a new brand love scale, then testing via survey (exploratory).
- Surveying digital trust, then interviewing consumers who show outlier responses (explanatory).
- Running parallel interviews and experiments to triangulate service failure recovery perceptions.

6.3 | When

Mixed methods are most suitable when:

- Research questions cannot be answered adequately with a single method.
- Both generalisability (quant) and contextual richness (qual) are required.
- The study aims to develop a new theory and also test it empirically.

6.4 | Where

Applications in marketing research include:

- Consumer research: understanding emerging phenomena like influencer credibility.
- Retailing: combining store-level sales data with consumer ethnographies.
- Digital marketing: integrating clickstream analytics with interviews on user experience.

6.5 | Who

The unit of analysis spans both strands:

- Quantitative strand: large samples of consumers, firms, or transactions.
- Qualitative strand: smaller purposive samples for depth.
- Integration requires transparency on who contributes to which part.

6.6 | How

- Mixed methods require explicit integration strategies:
- Merging: results compared during interpretation.
- Connecting: one strand informs the sampling or design of the next.
- Embedding: one strand provides supportive evidence within the other. Analysis may use joint displays (tables/figures showing how results align).

Mixed methods research requires platforms that can integrate qualitative and quantitative strands. MAXQDA, JMP provide modules for joint displays, data linking, and code–statistic integration. Researchers also use combinations such as SPSS or Stata (for quantitative strands) together with NVivo/ATLAS.ti (for qualitative strands). Open-source platforms such as R and Jamovi can be combined with RQDA for mixed-method extensions, making integration more transparent and reproducible (refer Table 7 for thresholds).

6.7 | Common Misuses of Mixed Methods

- Running two methods independently without integration.
- Treating the qualitative strand as superficial or symbolic (e.g., one or two interviews or not taking insights from interview and move ahead).
- Lack of transparency on sequencing, weighting, or rationale.
- Using mixed methods only to 'add flavour,' without genuine complementarity.

6.8 | Guidelines for Authors

Mixed methods reflect the reality that marketing problems are rarely one-dimensional. When designed rigorously, they bridge numbers and narratives, prediction and meaning. Their misuse comes from a lack of integration; their value lies in showing how different forms of evidence converge or diverge to enrich understanding.

7 | Configurational & Comparative Methods (QCA Family)

7.1 | What

Configurational methods examine how combinations of conditions jointly lead to an outcome, recognising that different pathways (equifinality) can produce the same result. They move beyond linear sufficiency (as in regression) by incorporating

TABLE 7 | Thresholds of adequacy for mixed method designs.

Design	Key thresholds	Use cases for marketing research
Sequential exploratory	Qualitative saturation (~20–30 interviews) before survey design; survey $N \geq 200$	Used in scale development (e.g., customer engagement, brand authenticity).
Sequential explanatory	Quantitative analysis first (power ≥ 0.80); follow-up qualitative sample sufficient to explain anomalies	Applied in digital trust/adoption studies.
Concurrent triangulation	Comparable weighting of strands; convergence analysis required	Ensures credibility by testing consistency across methods.
Embedded design	Nested strand justified (e.g., 10–15 interviews within survey of 500+)	Useful in CRM or loyalty research.
Multiphase	Transparent sequencing and integration; requires resources for multiple rounds	Applied in longitudinal brand-building studies.

Source: Authors.

TABLE 8 | Thresholds of adequacy for configurational and comparative methods (fsQCA and GQCA).

Method	Key thresholds	Notes for marketing research
fsQCA	Consistency ≥ 0.75 for sufficiency; coverage > 0.25. Fuzzy membership scores between 0 and 1.	Used to analyse multiple causal paths (e.g., omnichannel strategy success).
GQCA	Normalised data (0–1 range). Grey relational grade ≥ 0.6 indicates strong similarity. Requires reference and comparative series.	Applied when data is incomplete/uncertain but patterns must be compared (e.g., retail formats, consumer adoption under uncertainty).

Source: Authors.

causal asymmetry (what drives success may differ from what drives failure) (Fan et al. 2024).

- fsQCA (Fuzzy-Set Qualitative Comparative Analysis): Combines qualitative case orientation with quantitative set-theoretic logic. Cases are assigned fuzzy membership scores (0–1) to conditions, allowing the identification of sufficient and necessary combinations (Choi 2026; Huarng and Roig-Tierno 2016; Das et al. 2022).
- GQCA (Grey Qualitative Comparative Analysis): Rooted in grey system theory, GQCA transforms incomplete or 'grey' data into quantitative similarity measures, identifying the degree of closeness between reference and comparative series to evaluate outcomes objectively (Merminod et al. 2022).

Placing fsQCA and GQCA together as a distinct family of configurational and comparative methods recognises their shared focus on complex causality and alternative pathways to outcomes. Both methods differ fundamentally from traditional quantitative models that emphasise linear sufficiency and from qualitative designs that stress contextual narratives. fsQCA bridges the two traditions by combining case-oriented reasoning with set-theoretic quantification, whilst GQCA introduces robust comparative logic for incomplete or uncertain data through grey system analysis (Han, Wong, et al. 2025). Grouping them avoids forcing them into the conventional 'qualitative versus quantitative' divide but also highlights their collective contribution: enabling marketing scholars to capture equifinality, asymmetry, and uncertainty in ways that other methods cannot (Huarng 2016). The threshold values are presented in Table 8.

7.2 | Why

These methods are valuable because marketing outcomes are often complex, context-dependent, and non-linear. Configurational approaches allow scholars to capture:

- Equifinality: Different paths to the same outcome (e.g., high loyalty via either brand trust or switching costs).
- Asymmetry: The absence of conditions for success is not simply the mirror opposite of those for failure.
- Threshold sensitivity: Especially relevant in GQCA, which quantifies minimum levels of similarity or performance.

Examples:

- fsQCA: Identifying configurations of digital capabilities and managerial support that jointly drive successful omnichannel adoption.
- GQCA: Comparing competing retail formats under uncertain market data to identify the closest match to consumer preference patterns.

7.3 | When

Configurational methods are best applied in the following situations:

- The research question involves multiple interacting conditions.

- Theoretical frameworks suggest different pathways to outcomes.
- Data may be limited, uncertain, or incomplete (especially suitable for GQCA).

7.4 | Where

- Consumer research: fsQCA used to explore combinations of cultural values and social influence driving product adoption.
- Retailing: GQCA applied to benchmark alternative store formats under uncertain consumer demand.
- Digital marketing: fsQCA applied to understand different bundles of social media activities that drive engagement.
- B2B marketing: Both fsQCA and GQCA applied to analyse alliance success under uncertain environments.

7.5 | Who

Units of analysis may include:

- fsQCA: Firms, consumer groups, or countries (comparative cases with partial set membership). Sample size required is a moderate number of cases (often 10–50+).
- GQCA: Indicators or data series that must be compared quantitatively (e.g., multiple store performance indices). Works well with small datasets.

7.6 | How

fsQCA:

- Calibrate data into fuzzy sets (0–1 membership).
- Construct a truth table of conditions and outcomes.
- Simplify logical expressions using Boolean minimisation.
- Report consistency and coverage to assess sufficiency and necessity.

Formula (Consistency for sufficiency):

$$Consistency\ (X \le Y) = \frac{\sum \min\left(X_i, Y_i\right)}{\sum X_i}$$

GQCA:

Normalise data to a 0–1 scale.

- Compute grey relational coefficients between reference and comparative series.
- Derive the grey relational grade to rank alternatives.

Formula (Grey Relational Grade):

$$\gamma\left(x_0, x_i\right) = \frac{1}{n} \sum_{k=1}^{n} \frac{\min\ \Delta + \zeta \max \Delta}{\Delta_{0i}(k) + \zeta \max \Delta}$$

where $\Delta_{0i}(k)$ is the difference between reference and comparative series at point k; ζ is the distinguishing coefficient (0–1, usually 0.5).

fsQCA is supported by the dedicated fsQCA software developed at the University of Zurich, as well as Tosmana (for Boolean analysis) and R packages (QCA, SetMethods) (see Table 9). These allow calibration, truth table construction, and minimisation procedures. GQCA is less institutionalised but can be implemented using R (e.g., greyrel libraries), MATLAB, or Python packages for grey system analysis. Increasingly, scholars combine fsQCA outputs with SEM/PLS results to strengthen configurational insights.

7.7 | Common Misuses of Configurational Methods

- Treating fsQCA as purely qualitative or purely quantitative, ignoring its hybrid nature.
- Applying fsQCA with too few cases produces unstable truth tables.
- Using GQCA without proper data normalisation.
- Over-interpreting equifinal pathways without theoretical justification.

7.8 | Guidelines for Authors

Configurational methods provide marketing researchers with a distinctive lens to address complexity, uncertainty, and causal asymmetry. fsQCA bridges qualitative depth with quantitative set theory, whilst GQCA offers robust analysis under incomplete information. Their value lies not in replacing traditional methods but in complementing them, especially where multiple pathways exist, or data quality is uncertain.

8 | Big Data & Computational Methods

8.1 | What

Big data and computational methods address large, complex, and often unstructured datasets to answer what patterns exist in digital traces and how they can be leveraged for marketing insight.

- Text mining/NLP: topic modelling of reviews, sentiment analysis of tweets (Demydyuk et al. 2024).
- Social media analytics: examining brand conversations on platforms like Twitter, Instagram, and Reddit.
- Clickstream/web analytics: analysing user navigation paths on e-commerce sites.
- Image/video analytics: computer vision for logo detection, shelf analysis, influencer content.
- Machine learning: supervised (predict churn), unsupervised (segment consumers), deep learning (visual recognition, generative content).

TABLE 9 | Comparison of fsQCA and GQCA in marketing research.

Aspect	fsQCA	GQCA
Logic	Hybrid method combining qualitative case orientation with quantitative set membership.	Quantitative method based on grey system theory, suited to incomplete/uncertain data.
Data type	Case-level data with fuzzy set calibration (0–1 membership scores).	Time series or indicator data normalised to [0, 1] for comparison.
Purpose	Identifies sufficient and/or necessary configurations of conditions leading to an outcome.	Measures similarity/dissimilarity between reference and alternative series to rank options.
Key outputs	Truth table, consistency, coverage metrics; multiple causal pathways.	Grey relational coefficients and grades indicating closeness to reference.
Strengths	Captures causal complexity, equifinality, and asymmetry.	Handles incomplete/'grey' data; provides objective rankings.
Limitations	Sensitive to calibration and small samples; risk of over-complex models.	Less intuitive for theory-building; primarily comparison-based.
Marketing use cases	Examining multiple paths to digital adoption, loyalty, or innovation success.	Benchmarking retail formats, consumer preference structures under uncertainty.

Source: Authors.

- ANN (Artificial Neural Networks): Multi-layered computational models inspired by the human brain, used for pattern recognition, classification, and prediction. ANNs are widely applied in marketing for churn prediction, customer adoption modelling, sentiment analysis of reviews, and recommender systems (Zhao and Zhan 2025).
- Predictive modelling: conversion likelihood, recommendation systems (Kaurav and Thomas 2025).
- Network science: mapping social networks, brand communities, or knowledge flows.

8.2 | Why

The rationale is clear: digital marketing generates massive data streams, and traditional statistical methods are insufficient to capture their complexity. Big data methods allow marketing researchers to:

- Understand consumer sentiments at scale.
- Detect emerging trends in social networks.
- Predict churn, cross-sell, or conversion probabilities.
- Uncover hidden structures in consumer–brand interactions.

Examples:

- Sentiment analysis of TripAdvisor reviews to predict hotel ratings.
- Clickstream modelling to optimise checkout flows in e-commerce.
- Deep learning on Instagram posts to identify visual drivers of engagement.
- Network analysis of online brand communities to detect influencers.

8.3 | When

These methods are most suitable when:

- Data are high-volume, high-velocity, or high-variety (the '3Vs' of big data).
- Research questions involve prediction, pattern detection, or digital trace analysis.
- Traditional surveys or experiments are insufficient (e.g., analysing millions of tweets).

8.4 | Where

Applications span almost all domains of marketing:

- Consumer behaviour: analysing reviews, social media posts.
- Digital marketing: campaign targeting and optimisation.
- Retailing/CRM: churn prediction, recommendation engines.
- Branding: image recognition in user-generated content.

8.5 | Who

The unit of analysis is often digital consumers (users, customers, communities) or digital artefacts (posts, clicks, images). Sampling adequacy is less relevant; instead, the focus shifts to data representativeness and cleanliness. For ANN, preferably

TABLE 10 | Thresholds of adequacy for big data and AI-driven methods.

Method	Key thresholds	Use cases for marketing research
Text mining/NLP	Minimum corpus size: ≥1000 documents for topic stability; coherence score ≥0.5 for topic models	Used in review mining, brand sentiment studies.
Social media analytics	Adequate time window (≥3–6 months for trends); bot filtering essential	Applied in influencer and brand community studies.
Clickstream analytics	Session-level tracking; $N \geq 10{,}000$ sessions for robust models	Used in website optimisation and path analysis.
Image/Video analytics	Accuracy > 80% (precision, recall, F1 score); labelled dataset quality critical	Applied in shelf recognition, logo detection, ad effectiveness.
Machine learning (supervised)	Train/test split; cross-validation; accuracy/ROC-AUC > 0.70 desirable	Predict churn, conversion, adoption.
Machine learning (unsupervised)	Cluster stability indices (e.g., silhouette > 0.5)	Used in customer segmentation.
ANN	Performance Metrics: Accuracy, Precision, Recall, F1, ROC-AUC > 0.70 acceptable. Overfitting Checks: Cross-validation, dropout, regularisation. Interpretability: Increasingly addressed using SHAP, LIME, or feature importance.	Applied to churn prediction, adoption likelihood. Critical when data are limited. Important for managerial insights, not just prediction.
Deep learning	Requires large datasets (often > 10,000 images or text sequences); overfitting checks	Visual analytics, generative marketing content.
Predictive modelling	Out-of-sample validation; lift > 10% vs. baseline	Widely used in CRM targeting.
Network science	Density, centrality, modularity thresholds; robustness tests	Applied in influencer detection and brand community mapping.

Source: Authors.

large datasets (> 1000 observations); more are needed for deep architectures (refer to Table 10 for threshold values).

8.6 | How

- Data collection: APIs, web scraping, CRM systems.
- Preprocessing: cleaning, tokenisation, feature engineering.
- Analysis: machine learning algorithms, deep learning architectures, network metrics.
- Validation: cross-validation, out-of-sample testing, performance metrics.

Formula (neural network, simpler version):

$$y = f\,(Wx + b)$$

where W is the weights, x is the inputs (e.g., image pixels), b is the bias, f is the activation function.

Formula topic modelling (latent Dirichlet allocation, LDA):

$$p\,(w|\,d) = \sum \sum_{k-1}^{K} = (w|\,z = k).\,(p(z = k|\,d))$$

where $p(w|d)$ is the probability of word, w in document d, z is the latent topic, K is the number of topics.

Formula sentiment analysis (Naïve Bayes):

$$P(Sentiment \mid Words) \propto \mathrm{P(Sentiment)} \prod_{i-1}^{n} P\left(w_i \mid Sentiment\right)$$

Formula machine learning: Supervised learning (logistic regression, classification):

$$P(y = 1|\,X) = \frac{1}{1 + e^{-(\beta 0 + \beta 1 X 1 + \cdots + \beta k X k)}}$$

Unsupervised learning (k-means clustering):

$$MinC \sum_{i-1}^{n} \left\| x_i - \mu_{Ci} \right\|^2$$

where x_i is the data point, μ_{ci} is the cluster centroid.

Deep learning (Feedforward NN):

$$y = f(Wx + b)$$

where W is the weight matrix, b is the bias, f is the non-linear activation.

A variety of open-source and commercial platforms support computational marketing research. Python (libraries: NLTK, spaCy, gensim, scikit-learn, transformers) and R (tm, quanteda, tidytext) dominate text mining and sentiment analysis. NodeXL, Netlytic, Gephi, and UCINET are widely used for social media and network analytics. Google Analytics and Adobe Analytics provide industry-standard clickstream data analysis. Image and video analytics rely on TensorFlow, PyTorch, Keras, and OpenCV. Predictive modelling and clustering are facilitated by RapidMiner, Weka, Orange, and Python/R machine learning toolkits. For network science, Gephi, Pajek, and NetworkX (Python) are standard choices.

8.7 | Common Misuses of Big Data Methods

- Equating big sample size with representativeness (e.g., Twitter ≠ all consumers).
- Using algorithms as 'black boxes' without theoretical grounding.
- Ignoring data privacy and ethical considerations.
- Overfitting models without proper validation.

8.8 | Guidelines for Authors

Big data and computational methods expand what marketing researchers can study, from millions of consumer conversations to visual content and predictive analytics. Yet, their misuse often comes from prioritizing technical sophistication over theoretical alignment. When integrated with sound research design, these methods open unprecedented avenues for understanding and shaping markets. ANNs extend the researcher's toolkit for prediction and pattern recognition in marketing. Their power lies in modelling complexity, but their limitation is interpretability. Used thoughtfully, they complement theory-driven methods by revealing non-linear dynamics and generating actionable insights.

9 | AI-Driven Methods & Techniques

9.1 | What

AI methods in research involve algorithms that learn from data to classify, predict, generate, or optimise. They answer what patterns exist in high-dimensional consumer data and how intelligent systems can be applied to marketing problems (Paul 2024; AlBannai 2025).

- Natural Language Generation (NLG): Automated text generation for surveys, product descriptions.
- Generative AI (LLMs, diffusion models): Content creation, campaign design, synthetic respondents.
- Reinforcement Learning: Optimising sequential decisions (e.g., personalised promotions).
- Recommender Systems: Collaborative filtering, hybrid recommenders for customer choice modelling.
- AI-enabled Causal Inference: Uplift modelling, counterfactual prediction.
- Hybrid AI-Human Methods: AI-assisted coding of qualitative data, AI-augmented survey design.

9.2 | Why

AI is being incorporated because marketing data is increasingly unstructured, multimodal, and dynamic. Traditional methods cannot capture this complexity. AI techniques allow:

- Discovery of emergent consumer needs through unstructured text/image/video.
- Automated personalisation at scale.
- Simulated consumer decision-making under different scenarios.
- New ways to test theory using synthetic or augmented data.

Examples:

- Using transformer-based sentiment models to detect emotions in reviews.
- Applying reinforcement learning to optimise dynamic pricing in e-commerce.
- Leveraging generative AI to simulate customer responses in A/B testing.

9.3 | When

AI methods are most suitable when:

- Data is too large, complex, or unstructured for conventional statistics.
- Research questions require prediction, recommendation, or generative outputs.
- Real-time decision-making or adaptive experimentation is required.

9.4 | Where

- Consumer research: using AI to decode visual consumption signals from Instagram.
- Retailing: reinforcement learning for personalised in-store offers.
- Advertising: generative AI for ad copy and image variants.
- Services: chatbots and conversational AI as both objects of study and research tools.

9.5 | Who

Units of analysis shift from individuals to digital traces, synthetic consumers, or AI agents. In many cases, 'who' is both the consumer and the algorithm interpreting behaviour.

9.6 | How

AI methods are executed via pipelines:

- Data ingestion (text, images, voice, behavioural traces).
- Model training (supervised, unsupervised, reinforcement, generative).
- Validation (out-of-sample tests, fairness audits, interpretability).
- Deployment (as recommender systems, content generators, predictive models).

The popular Generative AI tools in research are ChatGPT (Paul, Khatri, and Kaur Duggal 2023), Claude, Jasper, Copy.ai, MidJourney, and Stable Diffusion. Transformer-based NLP models are available through Hugging Face Transformers, OpenAI API, Google Cloud NLP, and AWS Comprehend. Reinforcement learning can be implemented in Python (OpenAI Gym, RLlib), TensorFlow-Agents, or MATLAB Reinforcement Learning Toolbox. AI-assisted qualitative coding is being embedded into ATLAS.ti and MAXQDA, where machine learning aids the researcher whilst preserving interpretive validation (Table 11 offers the details for thresholds).

9.7 | Common Misuses of AI in Research

- Treating algorithms as 'black boxes' without theoretical grounding.
- Ignoring bias, fairness, and ethical thresholds in model training.
- Overclaiming generalisability from synthetic data.
- Using AI outputs as unquestioned 'truth' rather than triangulated evidence.

9.8 | Guidelines for Authors

AI is not just an additional technique but a transformation in how research is conducted. It redefines 'data,' introduces new units of analysis, and blurs the line between method and tool. Its promise lies in augmenting, not replacing, established research traditions—offering new forms of evidence whilst demanding even greater attention to thresholds, validity, and ethics.

10 | Literature Review as Research Method

Literature reviews are an integral part of doctoral and academic research (Paul and Criado 2020; Tomczyk et al. 2024). A good literature review offers insights into the evolution of the research field and helps understand theories, context, characteristics, and methods, and identifies research gaps (Paul and Barari 2022; Paul 2024). Researchers develop a future research agenda based on identified research gaps in a typical review paper (Paul, Ueno, and Dennis 2023; Paul 2025; Kaurav and Mishra 2024; Paul, Ueno, et al. 2024; Kaurav, Kulkarni, and Shee 2024).

10.1 | What

There are 3 Major types of reviews. 1. Domain-based review. 2. Theory-based review 3. Method-based review. Amongst these, domain-based reviews are more popular, and they can be further classified into 7 different types as follows (Paul and Criado 2020; Paul, Ueno, et al. 2024)

a. Narrative (plain Vanilla) review
b. Framework-based review using an Org Framework (Paul 2024; Hassan et al. 2022; Södergren 2021; Paul and Benito 2018)
c. Conceptual review aiming for theory development (Paul and Mas 2020 & Majority of the articles in the AMS Review & the Academy of Management (AoM) Review)
d. Bibliometric review (Pattnaik et al. 2020; Paul and Bhukya 2021; Kaurav and Gupta 2022)
e. Hybrid Review (Chakma et al. 2021; Kaurav et al. 2025)
f. Structured, but without an organizing framework (Dhaliwal et al. 2025; Rosado-Serrano et al. 2018)

10.2 | Why

The rationale for literature reviews as a method lies in their ability to consolidate fragmented knowledge and build future

TABLE 11 | Thresholds of adequacy for AI-driven methods.

Method	Key thresholds	Use cases for marketing research
Generative AI	Output validity must be human-verified; transparency of prompts and parameters	Applied in content creation, campaign testing.
NLP/transformer models	Accuracy/recall > 80%; explainability (e.g., SHAP values) desirable	Used in sentiment/emotion detection.
Reinforcement learning	Convergence to stable policies; reward > baseline strategy	Applied in dynamic pricing, personalised promotions.
AI-assisted qualitative coding	Agreement with human coders $\kappa > 0.70$	Speeds up analysis in netnography, interviews.

Source: Authors.

agendas. In social sciences, especially in marketing and business management research, rapid expansion of subfields, i.e., AI, sustainability, and digital platforms means that reviews are vital for:

- Establishing state of the art.
- Synthesising scattered findings.
- Clarifying constructs and measures.
- Identifying under-researched gaps.
- Developing integrative frameworks or theories.

Reviews also serve as entry points for doctoral students and new scholars, enabling faster immersion into a field.

10.3 | When and Where

It is important to note that bibliometric and hybrid reviews do not help identify research gaps; hence, other methods, such as developing a review using organizing frameworks, are considered to be better to serve the purpose of deriving research gaps to set a future research agenda, which has to stem from research gaps (Paul et al. 2021; Sahni and Kaurav 2023).

Researchers would find worth reading specimen articles for Theory-based review (Gilal et al. 2019, 2023; Shahid et al. 2024) and method-based review (Venkatesh et al. 2013; Diwanji 2023). Reviews are most appropriate when:

- A domain has grown fragmented or saturated with primary studies.
- New theories or phenomena have emerged, requiring conceptual clarity.
- Researchers seek to provide directions for future research (e.g., future research pathways).

Literature reviews are published in Q1 journals including AoM Review, Journal of the Academy of Marketing Science (JAMS), Journal of Business Research (JBR), and in the specialised outlets like AMS Review, International Journal of Management Reviews, Human Resource Management Review, Management Review Quarterly (MRQ).

10.4 | Who

The unit of analysis depends on the review type:

- Domain reviews: focus on industries, consumer segments, or marketing phenomena.
- Theory-based reviews: focus on a theoretical lens in a field. e.g., service-dominant logic stimulus-organism-response, value-attitude-behaviour.
- Method reviews: focus on research tools and techniques across studies, e.g., SEM, FSQCA in a specific field.

10.5 | How

Conducting a literature review involves:

- Systematic search strategy through databases like Scopus, Web of Science, you may use any one or a combination of these based on your requirements. This step is crucial as anyone can replicate the same study, if you are offering a clear search strategy.
- Inclusion/exclusion criteria for selecting articles.
- Coding and synthesis, either narratively (MAXQDA, NVivo, ATLAS.ti) or quantitatively
- Framework development, where constructs, theories, or findings are organised into a structured model (Required only in the case of Conceptual reviews)
- Gap identification leading to a future research agenda.

10.6 | Common Misuses of Literature Reviews

- Producing descriptive 'laundry list' reviews without synthesis.
- Over-reliance on bibliometrics without conceptual contribution.
- Failing to derive actionable research gaps.
- Using selective citation rather than systematic coverage.
- Treating reviews as easier or less rigorous than empirical research.

10.7 | Guidelines for Authors

When undertaking a literature review as a method, authors should begin by clearly articulating the type of review they intend to conduct—whether domain-based, theory-based, or method-based. Then, researchers can decide what type of domain-based review is to be conducted (Paul 2025). This clarity not only orients the reader but also sets expectations about the contribution. A rigorous review requires systematic protocols for identifying, screening, and including studies. Protocols and frameworks such as SPAR-4-SLR (Paul et al. 2021), POWER (Rana et al. 2022), TMCC, ADO (Sharma et al. 2024) can be adapted to ensure transparency in the selection process. In our opinion, PRISMA is repeatedly used and therefore, it has become redundant and replete without newness and novelty.

Beyond collecting articles, the review must be designed to synthesise rather than summarise. Employing conceptual or organising frameworks helps avoid the common pitfall of producing a descriptive 'laundry list.' Authors are encouraged to move from reporting what has been studied to explaining how findings connect, diverge, and evolve, thereby offering genuine insight.

Finally, every review should culminate in a clear and actionable research agenda. Future research directions must be derived explicitly from identified gaps, showing how they connect to theory, methods, or context. By providing specific pathways rather than generic calls, authors demonstrate both scholarly depth and practical utility. A literature review that follows these principles is not an easy shortcut but a robust methodological contribution, capable of advancing the discipline with clarity, credibility, and impact.

11 | Directions for Future Research

The recent pandemic, geo-economic and socio-cultural situations have resulted in structural changes in many sectors (Alagarsamy et al. 2022; Nayal et al. 2021). i.e., the pandemic has changed the way people think and the resultant consumer behaviour (Chakraborty and Paul 2022; Purohit et al. 2022; Chopdar et al. 2022). As an outcome, following experts (Basu et al. 2022; Kajol et al. 2022), we concur with the need for developing new and novel research methods, scales, and paradigms to carry out research studies in the post-pandemic era to analyse the new processes, patterns, and problems with a unique approach.

In a nutshell, the nine families of research methods reflect both the breadth and the evolution of marketing inquiry. Quantitative approaches provide precision, measurement, and hypothesis testing, whilst qualitative methods illuminate meaning, context, and the lived realities of consumers. Mixed methods integrate these traditions, demonstrating how numbers and narratives can complement one another rather than compete. Big data and computational techniques extend the scope further, enabling the analysis of high-dimensional, real-time, and unstructured data that traditional tools struggle to accommodate. AI-driven methods advance this frontier still further, reshaping not only how data are analysed but also how insights are generated, predictions refined, and marketing strategies personalised. Each family is distinct, yet none is sufficient in isolation. The choice of method is not a matter of hierarchy but of alignment, ensuring that the what, why, when, where, who, and how of the research question converge with the method's underlying logic and adequacy thresholds. Taken together, these families provide scholars with a versatile toolkit that balances tradition with innovation, rigour with relevance, and theoretical explanation with predictive power.

Traditional designs, qualitative inquiry, mixed approaches, computational analytics, and AI-driven techniques all offer unique possibilities, but their value lies not in novelty or technical

TABLE 12 | Mapping research methods to the research journey (5WH lens and integration pathways).

Stage of research (When)	Primary purpose (What/Why)	Typical methods (How/Who/Where)	Possible integration (multi-stage/multi-study)
Exploration (early stage)	Generate insights, identify constructs, contextual understanding	Qualitative methods: case study, ethnography, grounded theory, phenomenology, focus groups	Can feed into survey design (quantitative), provide variables for SEM, or integrate with netnography or digital ethnography before large-N analysis
Measurement development	Scale development, construct validation	EFA, CFA, reliability analysis	Followed by SEM for structural testing, combined with qualitative insights for item refinement
Hypothesis testing & causal inference	Test relationships, mediation, moderation, causal effects	Regression (linear, logistic, multilevel), experiments (lab, field, quasi)	Can be triangulated with qualitative case findings; often combined with SEM for theory-driven testing
Comparative/ configurational analysis	Understand multiple causal pathways, 'equifinality'	fsQCA, GQCA	Can complement regression/SEM by showing alternative paths; often combined with case studies for richer context
Synthesis & review	Consolidate existing knowledge, identify gaps	Systematic reviews, bibliometrics, meta-analysis (Tripathi et al. 2024)	Can be integrated as a prelude to empirical research, or post-project validation of generalisability
Big data & computational analytics	Analyse large-scale, real-time, unstructured data	Text mining, social media analytics, clickstream, image/ video analytics, ML/AI	Can be embedded within survey/ experimental data; often combined with qualitative interpretation for context
AI-driven research	Prediction, personalisation, content generation, adaptive modelling	Generative AI, reinforcement learning, transformer models	Can be combined with experiments (AI-generated stimuli), qualitative coding (AI-assisted), or predictive modelling for CRM/retailing
Integration stage	Synthesise across methods for robustness	Multi-method/multi-study design	Sequential (qual → quant, or quant → qual), concurrent triangulation, embedded studies, or multiphase designs

sophistication alone. The enduring question needs to be answered scientifically: *Is the method aligned with the research problem?*

To further consolidate the 5WH framework, Table 12 provides a roadmap that situates different families of methods along the research journey. It highlights not only when and why a method is most relevant, but also how it can be integrated with others in multi-stage or multi-study designs. This integrative view emphasises complementarity rather than hierarchy, encouraging researchers to align their methodological choices with both their questions and broader research programmes.

As Table 12 illustrates, methods rarely operate in isolation. Stronger contributions often emerge when exploration leads into measurement, measurement into testing, and testing into integration with computational or AI-driven tools. This journey underscores a central point: no method is complete on its own, and methodological rigour in consumer and marketing research increasingly comes from thoughtful sequencing and integration across traditions.

12 | Conclusions

This article provides a simple yet rigorous compass for answering this question. *What* clarifies the object of inquiry, *why* justifies its purpose, *when* and *where* situates it in context, *who* identifies the unit of analysis, and *how* specifies the design and execution. Thresholds—whether statistical, procedural, or ethical—ensure adequacy and guard against fragility.

For researchers, the 5WH framework serves not only as a technical guide but also as an epistemological bridge: *it resists the tendency of methods discourse to drift either into abstract philosophy or narrow technicality*. By grounding choices in comparative reasoning, it helps reconnect the logic of inquiry with the problems that research is meant to address.

The framework thus enables authors to justify choices with clarity and equips reviewers and editors with a common lens for evaluating methodological fit. Yet one truth stands out across traditions old and new: *no single method is ever complete in itself*. Robust contributions often emerge from multi-study designs or multi-stage research programmes, where different methods converge to provide stronger evidence. By embracing this integrative spirit, researchers can balance rigor with relevance, tradition with innovation, and methodological diversity with epistemological coherence.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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