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Why Gen Z Buying Research Keeps Agreeing – And why that's a Problem?

Sabiya Shaikh[1*], Chetna Narendra Mehta[2], Kota Madhusudhana Rao[3], P. C. K. Rao[4]

[1](PhD – Research Scholar), Asst. Professor, School of Management, Ajeenkya DY Patil University, Pune, Maharashtra, India
[2]Professor, Dean & Researcher (Management), School of Management, Ajeenkya DY Patil University & Tata Institute of Social Sciences, Pune, Maharashtra, India;
ORCID: 009-0001-0871-2614
[3]Asst. Professor, Department of Humanities and Sciences, Faculty of Science and Technology, ICFAI Foundation for Higher Education, Hyderabad, India;
ORCID: 0009-0008-6738-8632
[4]Professor (Leadership and Project Management), Institute of Advanced Research in Management Sciences, Delhi (NCT), India;
ORCID: 0000-0003-3054-7384
***Corresponding Author**:
Email ID: sabia.shaikh@adypu.edu.in

ABSTRACT
The influence of social media marketing on Gen Z buying decisions tremendously soared during the past decade and that triggered the researchers across to investigate into the determinants. The research outcomes revealed that there is a closer link between credibility, trust, engagement, and electronic word-of-mouth with the purchase intentions and decisions of these consumer groups. Consequently, a question arises: does those revelations reflect genuine buying behaviour or a result of repeated use of similar research methodology in the field?
This paper presents a realist-informed integrative review of 150 peer-reviewed empirical studies published between 2010 and 2025. Unlike prior reviews, this considers studying dominant methodological patterns and explain their persistence through context-mechanism-outcome (CMO) configurations. Guided by PRISMA for selection and a structured coding framework, the review reveals that the researchers persistently chose cross-sectional surveys, convenience sampling, self-reported purchase intentions, and PLS-SEM opuses which eventually landed in mesmerizingly coherent results.
Cross-tabulations, temporal trends, and realist refinement shows these patterns are not random but structurally reinforced by publication incentives, analytical familiarity bias, and path dependence. The result is an illusion of consensus that side-lines behavioural, longitudinal, and qualitative insights.
By exposing how methodological choices actively constitute knowledge, the study clarifies the conditions shaping current evidence. Further the study proposes targeted means for journal incentives, training reforms, hybrid designs to enable more diverse, realistic, and relevant future research on Gen Z buying behaviour.
Keywords: Gen Z, social media marketing, purchase decisions, methodological review, realist synthesis, integrative review, research design, purchase intention, behavioural realism, PLS-SEM

INTRODUCTION:

Social media isn't just a tool anymore it's the heartbeat of how Generation Z (Gen Z) lives, connects, and decides what to buy (Barucha, 2018). This group of consumer segment grew up with phones in their hands, Instagram feeds and snapchats shaping their tastes, TikTok and Popcorn short reels sparks instant wants, delivering a feel more like friends than advertisements (Bhalla, Tiwari, & Chowdhary, 2021). For brands, this makes social media the single most important place to reach them, making the conventional ones almost old-school (Panopoulos, Poulis, Theodoridis, & Kalampakas, 2022). No wonder researchers have been pouring energy into understanding how social media marketing actually sways Gen Z's buying choices over the last decade (Chakola, 2023); (Djafarova & Bowes, Instagram made me buy iit: Generation Z impulse purchaases in fashion industry, 2021). Much of the literature from the extant research, concludes (Djafarova & Rushworth, 2017) that what continues to arise in study after study is pretty consistent: influencer endorsements, user-generated content, interactive brand posts, and online word-of-mouth etc., which in turn build trust, ignites positive feelings, and tunes Gen Z impulsive (Lashari, 2025); (Sardar & Vijay, 2025); (Lou & Yuan, 2019); (Ki & Kim, 2019).

Yet the consistency of results invites closer scrutiny. Despite rapid changes in platform architectures, (Bonina, Koskinen, Eaton, & Gawer, 2021) content formats, and user practices, empirical conclusions have remained remarkably stable (De Reuver, Sørensen, & Basole, 2018). New studies often replicate established relationships using similar models, measures, and samples, with limited variation in research design or analytical approach. All this appears to be like 'old wine in the new bottle'. This raises a fundamental question that has received little attention: "*to what extent is current knowledge on Gen Z buying intentions vis-à-vis social media marketing corroborate theoretically, and methodically beyond any empirical discovery*"?

Prior reviews in this area have largely focused on cataloguing constructs, covering theoretical perspectives, or summarising reported effects (Gurrieri, Drenten, & Abidin, 2024); (Sokolova & Kefi, 2020); (deVeirman, Cauberghe, & Hudders, 2017). Despite being solidly pursued, such reviews tend to treat research methods as neutral tools rather than as constitutive elements to disseminate the knowledge. However, long-standing methodological designs suggests that what researchers choose to measure, whom they study, and how they analyse data directly shapes what can be known about consumer behaviour (Charness, Gneezy, & Kuhn, 2012).

Perhaps it straightjackets disciplines which are highly dynamic and homogeneous, application of similar research methods repetitively can lead to what constitutes as an "illusion of consensus," depicting agreement in findings reflects methodological myopia than robust explanatory power (Aljafari, 2019). Research on Gen Z and social media marketing exhibits several features associated with this risk, including heavy reliance on cross-sectional surveys, convenience sampling, and self-reported intention-based outcomes (Britt, Hayes, Britt, & Park, 2020).

Precisely, this work is undertaken to conduct a systematic methodological content analysis and review the prior empirical studies by retrieving publications between 2010 and 2025 on Gen Zs buying intentions. By detailing patterns in research objectives, sampling practices, measurement choices, analytical techniques, and temporal framing, the study seeks to clarify the methodological vortex.

In doing so, the paper contributes to the literature in two ways. First, it uncovers a structured and transparent methodological practices often applied in the field. Second, it surfaces the ground for more reflective and diversified research to be followed duly benchmarking areas of methodological canons limiting analytical insights.

Since the early 2010s, good amount of research has examined how social media marketing through influencer endorsements (Choi & Rifon, 2012), interactive content, user-generated posts, and electronic word-of-mouth. It was found that consumers' attitudes, trust, and purchase intentions were among the most significant determinants that got shaped by such influencers.

Prior reviews have mapped key constructs, theories, and effects, treating methods largely as unbiassed tools (Bowledg, 2017). However, diverse methodologies remind that design decisions about what is measured, who is sampled, how data got analysed actively constitute knowledge, often benefiting certain perceptions while limiting others (Phillips, 2023). In homogeneous disciplines, heavy reliance on cross-sectional surveys, convenience samples, and intention-based outcomes can foster a deceptive agreement that stems from the self-declared constraints than the true facts and figures (Kitchin, 2014).

In a way, this paper addresses that black hole through a realist-informed integrative review of 150 empirical studies published from 2010 to 2025. The core purpose is not to synthesise on what social media marketing "does" to Gen Z consumers, rather to integrate diverse evidence and map widely used methodology to clarify the reasons of such persist application statistically (e.g., theoretical and resource limits), analytically (e.g., accessible to tools and familiarity, publication strings), and resultantly (e.g., pruned behavioural insight) as a sustainable outcome.

Background of the Study

Academic interest in social media marketing emerged alongside the rapid diffusion of social networking platforms in the late 2000s and early 2010s. Early research focused primarily on how social media changed in the means of communication between firms and consumers, emphasising interactivity, user participation, through shifting from firm-generated to user-generated content (Tyrväinen, Karjaluoto, & Ukpabi, 2023); (Chen, Wang, & Wei, 2025). Ever since social media platforms like Facebook, YouTube, and Instagram, snapchat, and twitter invaded everyday buying scenarios, marketing research is forced to question the power of influence, persuasion, and value creation in digital environments (Wroblewski, 2024).

Within this broader trajectory, Gen Z emerged as a distinct segment to delve. Unlike previous generations (Gen X, Millennials), Gen Z consumers are identified as digital natives (Gupta, Gaur, Bhatt, Gaur, & Parveez, 2024) whose social, informational, and commercial activities are intertwined with social media platforms (Wandhe, 2924). Their day-to-day engagement and familiarity with social media evolve the culture, and sensitivity to authenticate focal group for research on such media–driven buying behaviour (Daiya & Roy, 2016).

By the mid-2010s, empirical studies examining the relationship between social media marketing and Gen Z's purchase decisions started to get recognised. Much of this work sought to identify the determinants of social media marketing which proved vital in influencing their consumer decisions (Waworuntu, Mandagi, & Pangemanan, 2022). Some of the vital torrent include credibility and attractiveness, trust and perceived authenticity, electronic word-of-mouth , information value and entertainment value (Wahdiniawati, Apriani, & Orlando, 2024), and other subsidiary means of engagement and interaction (KIEU, 2025).

Interestingly, throughout the literature, a single most construct was found considered by the researchers and i.e. 'purchase intention' than any other dependent variable. Though other similar studies used it as a proxy for buying decisions along with attitudes, brand loyalty, and trust on the transaction-linked measures but were inconsistent and dismal (Singh, Bajracharya, Rijal, & Shrestha, 2024). That means, most of the outcomes on Gen Z's purchase decisions in social media contexts is mainly derived out of intention-based information.

On the methodology side, cross-sectional survey combined with quantitative approach dominated the research throughout. The second-generation statistical tools such PLS-SEM and CB-SEM were majorly employed by the researchers to draw the results and analyse (Hair J. , Hult, Ringle, & Sarstedt, 2014). Often, they are found justifiable for theory testing, sample-size flexibility, or exploratory objectives, more particularly in emerging research trends. Convenience and purpose sampling techniques were considered in most of the studies tapping student community and platform-specific user groups to collect the primary data (Gross & Malzhacker, 2023).

The consistent use of these methodologies alarms towards their ascendency amongst the research designs eventually marginalising others which might be more revealing (Shevchenko, Kuhlmann, & Reips, 2021). Another major threat of heavy reliance on a unified set of methodologies could paralyse the accessibility to the root of the cause-and-effect relationship. When fields rely heavily on similar samples, measures, and analytical models, findings may converge not because the phenomenon is fully understood, but because alternative perspectives remain methodologically inaccessible (Power, Velez, Qadafi, & Tennant, 2018).

Several scholars have raised related concerns in adjacent domains of marketing and management research. In another study it was highlighted how common method variance can inflate observed relationships in survey-based studies (Aguinis, Ramani, & Alabduljader, 2018) while some other scholars demonstrated how methodological homogeneity can contribute to an illusion of theoretical consensus (Delios, et al., 2025). In social media research more specifically, it was observed that a strong dependence on self-reported data and cross-sectional designs, calling for greater methodological diversity to capture the dynamic and contextual nature of digital interactions (Wolgast, Adler, & Wolgast, 2025).

Despite these broader discussions, research focusing specifically on Gen Z and social media marketing has rarely subjected its own methodological foundations to systematic scrutiny. Reviews in this area have primarily synthesised constructs, platforms, or outcomes, offering valuable overviews but leaving underlying research practices largely unexamined (Hulland, Conceptual review papers: revisiting existing research to develop and refine theory, 2020). Consequently, there remains limited clarity regarding how methodological choices have shaped prevailing conclusions about Gen Z's purchase behaviour.

Against this backdrop, a focused examination of methodological patterns within this literature is both timely and necessary. As the volume of research continues to grow, understanding how evidence has been generated becomes essential for interpreting existing findings and for guiding future inquiry. This study responds to that need by systematically documenting and analysing the methodological characteristics of empirical research on social media marketing and Gen Z's purchase decisions over the period 2010–2025.

Statement of the Problem

Over the past fifteen years, research examining the influence of social media marketing on Gen Z consumers' purchase decisions has expanded rapidly. This growth has produced a substantial body of empirical evidence identifying a range of determinants such as influencer credibility, content characteristics, trust, engagement, and electronic word-of-mouth as drivers of purchase intention and related outcomes. While these findings have contributed meaningfully to theory and practice, the field now exhibits signs of methodological saturation rather than cumulative understanding.

A central problem lies not in the absence of research, but in the recurring use of similar methodological choices across studies. A large proportion of empirical investigations rely on cross-sectional survey designs, convenience-based samples (often student or platform-specific users), self-reported measures, and intention-focused dependent variables (Kamboj, Matharu, & Gupta, 2023). Analytical techniques such as structural equation modelling or partial least squares estimation are repeatedly applied to test closely related models using overlapping constructs. As a result, empirical diversity remains limited despite the growing volume of publications (Xu & Zhang, From contextulaizing to context theorizing: Assessing context effects in privacy research, 2022).

This methodological convergence raises critical concerns about the nature of the knowledge being produced. When similar methods are used to answer similar questions with similar samples, findings may appear consistent while still offering a narrow view of the phenomenon (Turner, Cardnal, & Burton, 2017). Prior methodological scholarship cautions that such patterns can reinforce dominant assumptions, obscure contextual variation, and limit theoretical development (Lambert & Newman, 2023). In the context of Gen Z research, this risk is particularly salient given the group's heterogeneity across cultures, platforms, and consumption contexts.

Moreover, existing studies often frame purchase decision-making as a stable, measurable outcome, captured at a single point in time. This treatment overlooks the dynamic and iterative nature of social media–based consumption, where exposure, engagement, social validation, and purchasing unfold over extended periods and across multiple platforms (Xu, Zhang, & Zhou, 2020). The dominance of intention-based metrics further complicates interpretation, as intentions do not always translate into behaviour, particularly in digital environments characterised by impulsive and socially mediated consumption (Priporas, Stylos, & Fotiadis, 2017).

Despite these issues, the field has yet to undertake a systematic examination of how methodological choices themselves shape research findings. Existing reviews have largely focused on identifying influential variables, platforms, or theoretical frameworks, offering descriptive syntheses rather than critical assessments of research design, sampling logic, measurement practices, and analytical strategies (O'Connell, McCoach, & Bell, 2022). Consequently, there is a fog surrounding those revelations whether to be considered as observed patterns in the literature regarding the behaviour of Gen Z consumers or the methodology grindings.

Scope and Analytical Orientation

This review examines empirical research on social media marketing and Gen Z purchase decisions published between 2010 and 2025, with a deliberate focus on the methodological configurations through which empirical claims in this field have been produced. (Alam, Haq, Kokash, Ahmed, & Ahsan, 2025). The analysis is bounded to peer-reviewed studies and treats individual articles as units of methodological assessment rather than sources of substantive effect synthesis. The review systematically maps patterns in research design, sampling strategies, measurement approaches, data sources, analytical techniques, and reporting conventions, with the objective of identifying recurring methodological configurations and their distribution over time (Vrontis, Makriides, Christofi, & Thrassou, 2021). Consistent with this orientation, the review does not evaluate the relative importance of specific determinants such as influencer credibility or engagement (Aldlimi, Priporas, & Chang, 2025). Instead, it examines how methodological choices may have shaped the repeated emergence and apparent salience of constructs within the literature (Pradhan, Kishore, & Gokhale, 2023).

Analytical Questions

Guided by this review scope, the study is organised around a set of analytical questions designed to structure the methodological assessment in a systematic and replicable manner. These questions do not seek causal explanations but instead aim to reveal domain-specific regularities and omissions.

AQ1: What research designs have been often used by the prior researchers to study the influence of social media marketing on Gen Z's purchase decisions between 2010 and 2025?

AQ2: What sampling strategies and sampling framework were employed to collect the primary data to test those variables during their empirical observations?

AQ3: What types of data sources and measurement approaches were most frequently employed?

AQ4: What analytical tools and techniques were most sought to analyse the data and how do they attempted to merge their stated objectives with that of their results obtained?

AQ5: What methodological assumptions and limitations recur across studies, and how are they addressed in reporting?

AQ6: What methodological gaps and underexplored approaches emerge from the cumulative evidence?

Search Strategy

This review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page M. , et al., 2021). Although the present study does not aim to statistically aggregate effect sizes, the PRISMA framework was adopted to ensure transparency, replicability, and methodological discipline in the identification, screening, and inclusion of studies. The protocol guided decisions related to database selection, search string formulation, eligibility criteria, screening stages, and final study inclusion. The unit of analysis for this review is published empirical studies, rather than individual respondents or datasets.

Database Selection

A comprehensive search was conducted across multiple academic databases to capture all those double-blind peer-reviewed research papers published between 2010 and 2025. The following databases were selected due to their relevance to marketing, management, consumer behaviour, and information systems research: Scopus, Web of Science, ScienceDirect, Emerald Insight, SpringerLink, Taylor & Francis Online, MDPI to list a few. These databases collectively cover a wide range of high-impact journals in marketing, business, communication, and digital media studies, reducing the risk of database-specific bias.

Search Strings

Search strings were developed iteratively to balance breadth and precision. Keywords were grouped into three core conceptual blocks: (1) Gen Z, (2) social media marketing, and (3) purchase decision-related outcomes. Boolean operators and truncation were used to accommodate variations in terminology.

Search strings such as ("Generation Z" OR "Gen Z" OR "Zoomers") AND ("social media marketing" OR "social media advertising" OR "influencer marketing" OR "digital marketing" OR "social networking sites") AND ("purchase decision" OR "purchase intention" OR "buying behaviour" OR "consumer decision") are used. Search strings were adapted slightly across databases to conform to platform-specific syntax requirements. Searches were limited to titles, abstracts, and keywords to ensure conceptual relevance.

Inclusion and Exclusion Criteria

Following the PRISMA 2020 guidelines, analytical consistency, and replicability, explicit eligibility criteria were considered important applied throughout the screening process (identification, screening, eligibility, inclusion) (Page M. , et al., 2021). Studies were included if they met all of the following: (1) peer-reviewed journal articles published in English between January 2010 and December 2025; (2) empirical studies (quantitative, qualitative, or mixed-methods); (3) explicit and primary focus on Gen Z consumers; (4) examination of social media marketing–related stimuli or interactions (e.g., influencer endorsements, user-generated content, interactive brand communication); and (5) inclusion of purchase decision–related outcomes (e.g., purchase intention, buying behaviour, brand choice, or attitude toward purchase).

Studies were excluded if they were conceptual papers, editorials, book chapters, dissertations, or conference proceedings; focused solely on millennials or mixed groups having no segregation of Gen Z analysis; addressed social media use without a marketing or consumer related aspects; or were not published in English. These criteria were applied rigorously at the title/abstract and full-text stages to maintain a precise and defensible corpus of final 150 studies.

Table 1: Summary of Inclusion and Exclusion Criteria

Criterion Type	Inclusion Criteria	Exclusion Criteria
Publication	Peer-reviewed journal articles (English), 2010–2025	Conceptual papers, editorials, book chapters, dissertations, conference proceedings; non-English articles
Study Type	Empirical (quantitative, qualitative, mixed-methods)	Non-empirical work
Population	Explicit and primary focus on Gen Z consumers	Millennials or mixed generations without separate Gen Z analysis
Focus	Social media marketing stimuli or interactions	Social media use without marketing/consumption focus
Outcome	Purchase decision–related outcomes (e.g., intention, behaviour, brand choice)	No purchase-related outcomes

PRISMA Flow Description

The database search yielded a total of 1,842 records across all sources. After removing 412 duplicate records, 1,430 unique articles remained for title and abstract screening. During the screening stage, 1,137 records were excluded due to lack of relevance to Gen Z, absence of a social media marketing focus, or non-consumption-oriented outcomes. The full texts of 293 articles were assessed for eligibility. Of these, 143 articles were excluded for reasons including:

(a) absence of explicit Gen Z analysis,

(b) conceptual or non-empirical nature,

(c) lack of purchase decision–related variables, or

(d) insufficient methodological transparency.

Following the eligibility assessment, a final sample of 150 empirical studies was retained for coding and analysis.

Table. 2: PRISMA Flow Summary

PRISMA Stage	Description	Number of Records
Identification	Records identified through database search	1,842
Identification	Duplicate records removed	412
Screening	Records screened (titles & abstracts)	1,430
Screening	Records excluded	1,137
Eligibility	Full-text articles assessed	293
Eligibility	Full-text articles excluded	143
Included	Studies included in final review	150

Research Methodology

This study adopts a systematic methodological content analysis approach, treating published empirical articles as the primary units of analysis (Dumay & Cai, 2014). Methodological content analysis is a well-established approach for examining research practices, design choices, and analytical patterns across bodies of literature (Riffe, Lacy, Watson, & Lovejoy, 2023). Unlike narrative reviews, this approach relies on explicit coding rules, predefined categories, and replicable procedures (Peng, Wang, Xu, Dai, & Yu, 2024). The purpose of the analysis is not to evaluate the substantive correctness of individual findings, but to document field-level methodological patterns and assess how recurring design and analytical choices shape cumulative knowledge in research on Gen Z, social media marketing, and purchase decisions (Heugens & Lander, 2009).

Development of the Coding Framework

The coding framework was developed through a three-stage process to ensure conceptual clarity and analytical completeness.

Preliminary Scoping: An initial subset of 30 studies was examined to identify recurring methodological features reported across papers. This scoping phase focused on sections commonly dealing with methodology and research design, sampling, measurement stats, and related data analysis techniques (Debernardi, 2025).

Category Construction: Subsequently, a well-designed coding scheme got developed by duly aligning with methodology and literature in marketing and management research (Hair, Sarstedt, Matthews, & Ringle, 2016). Categories were designed to be mutually exclusive, collectively exhaustive, and observable from published reports (Turner, Cardnal, & Burton, 2017).

Refinement and Validation: The framework was refined competently by using additional studies and resolving confusions in category definitions. Only variables that could be consistently identified across the full sample were retained, ensuring comparability and reliabilit

Table 3: Coding Framework – Six Primary Methodological Dimensions

Dimension	Description & Focus	Categories / Variables Coded	Purpose / Assessment Target
1. Research Design	Primary orientation of the study	Cross-sectional quantitative, Longitudinal quantitative, Experimental / quasi-experimental, Qualitative (e.g., interviews, focus groups, ethnography), Mixed-methods	Captures temporal structure and inferential strength
2. Sampling Strategy & Sample Characteristics	Key sampling and sample attributes	Sampling method: convenience, purposive, stratified, snowball, probabilistic, Sample size range (e.g., <200, 200–399, 400–699, ≥700) Population source: students, general consumers, platform-specific users Geographic context: single country vs. multi-country	Assesses representativeness and external validity
3. Data Source & Data Type	Primary origin of the analysed data	Self-reported survey data, Experimental stimulus-response data, Interview / qualitative narrative data, Platform / behavioural data, Secondary / archival data	Evaluates reliance on perceptual vs. behavioural evidence
4. Operationalisation of Purchase Decision	How the dependent construct (purchase decision-making) was measured	Purchase intention, Attitude toward purchase, Self-reported buying behaviour, Actual / observed purchase behaviour (Primary dependent variable coded when multiple outcomes present)	Examines proxy vs. direct measurement of decision-making
5.Analytical Techniques	Main method used for hypothesis testing or theme derivation	Descriptive statistics / regression, Covariance-based SEM (CB-SEM) - Partial least squares SEM (PLS-SEM), Experimen	Assesses alignment between research questions, data structure, and analysis

		tal analysis (e.g., ANOVA, manipulation checks), Qualitative thematic / content analysis	
6.Methodological Transparency & Limitations	Explicit reporting of key quality indicators	Sampling justification, Treatment of common method bias, Discussion of limitations, Claims regarding generalisability (Binary: reported / not reported)	Captures reporting quality and acknowledgment of constraints

Table 3 summarises on each dimension to include operationalised categories / variables and its core analytical purposes. All coding was based solely on explicit information in the original articles; absent details were coded as "not reported" for conservatism.

Coding Procedure

All studies were coded manually using a structured coding sheet developed in spreadsheet. Each article was read in full, with particular attention to the methodology, data analysis, and limitations sections. Coding decisions were based solely on explicit information reported in the article (Villiger, Schweiger, & Baldauf, 2022). No assumptions were made where methodological details were absent; such cases were coded as "not reported." This conservative approach avoids speculative interpretation and preserves auditability. Coding rules, category definitions, and decision examples were furnished in a codebook before full-scale coding began and applied consistently across the entire sample (Hair J. , Hult, Ringle, & Sarstedt, 2017); (Short, 2009). Studies were processed in batches of 20–25 to maintain focus and consistency. To assess intra-coder reliability, a random 20% subsample (n=30) was re-coded after a 14-day interval, yielding Cohen's kappa = 0.89 overall (strong agreement across dimensions) (Konkol, Nüst, & Goulier, 2020).

Reliability and Auditability

Although the review relies on published material rather than subjective interpretation, reliability was addressed through procedural transparency. Coding categories were operationally defined, decision rules were fixed in advance, and all coded variables are traceable to specific sections of the original articles. This design allows independent researchers to replicate the coding process using the same dataset and framework. The objective of reliability in this context is replicability of classification, not inter-rater agreement on interpretation.

Analytical Strategy

Following coding, the analysis proceeded in three steps:

- Descriptive mapping of methodologies across the full sample
- Cross-tabulation of key dimensions
- Temporal analysis to identify shifts in methodologies over the reviewed period

Results are reported using frequency distributions, percentage shares, and comparative summaries, consistent with the study's descriptive and evaluative objectives.

Coding Results: Field-Level Methodological Patterns

The results from coding 150 studies reveal distinct similarities across dimensions, confirming the studies homogeneity. These patterns, summarised below with key metrics from the coded dataset, highlight structural regularities that underpin the apparent agreement.

Table 4. Distribution of Research Designs (n = 150)

Research Design	Number	Percentage	Not Reported
Cross-sectional quantitative	108	72.0%	2.0%
Experimental / quasi-experimental	14	9.3%	–
Longitudinal quantitative	6	4.0%	–
Qualitative	12	8.0%	–
Mixed-methods	10	6.7%	–

Table 4 clearly display the cross-sectional designs overwhelmingly dominate (72%), with designs capable of capturing temporal or causal dynamics (longitudinal, experimental, mixed) collectively under 20%. This superficiality is not incidental rather aligns with convenience-driven practices that ploy on resource constraints and publication speed incentives which eventually pushes for a quick run data collection.

Table 5. Sampling Strategies Used

Sampling Method	Number	Percentage	Not Reported
Convenience	92	61.3%	15% (method)
Purposive	28	18.7%	–
Snowball	12	8.0%	–

Stratified / quota	10	6.7%	–
Probabilistic	8	5.3%	–

The table 5 shows that non-probability sampling is dominant in over 80% of studies, with convenience alone accounting for 61%. High "not reported" rates for method justification (15%) further alarms external validity concerns. This pattern reinforces a cycle where accessible subgroups (students, platform users) become proxies for "Gen Z," thereby limiting the universal and reflective path-dependencies.

Table 6. Sample Size Distribution

Sample Size Range	Number	Percentage
< 200	34	22.7%
200–399	56	37.3%
400–699	42	28.0%
≥ 700	18	12.0%

It can be seen in the table 6 that sizes cluster in the 200–699 range (65%), usually enough to conduct PLS-SEM but rarely exceeding thresholds for robust population inference. Sample size appears method-led (e.g., SEM requirements) rather than phenomenon-led, illustrating how analytical techniques shape upstream decisions

Table 7. Operationalisation of Purchase Decision

Outcome Measure	Number	Percentage	Not Reported
Purchase intention	101	67.3%	3%
Attitude toward purchase	26	17.3%	–
Self-reported buying behaviour	17	11.3%	–
Actual / observed behaviour	6	4.0%	–

Table 7 reveals that purchase intention dominates (67%), serving as a proxy for decision-making in most studies. Actual behaviour is statistically negligible (4%), despite social media's role in impulsive, real-time consumption. This intention-behaviour gap is structurally embedded with cross-tab analysis showing 81% of intention measures occur in cross-sectional designs, highlighting methodological convenience over behavioural realism.

Table 8. Analytical Techniques Employed

Method	Number	Percentage	Not Reported
PLS-SEM	68	45.3%	5%
CB-SEM	28	18.7%	–
Regression-based	22	14.7%	–
Experimental analysis	14	9.3%	–
Qualitative analysis	18	12.0%	–

PLS-SEM is the clearly considered method with 45% of the cases, employed in non-probability samples and intention outcomes. This reflects analytical familiarity and flexibility with smaller yet complex models and channelises through perceptual constructs contributing to stable but narrow conclusions.

Cross-Tabulation Analytical Results

Cross-tabulations uncover how methodological decisions are not independent but interdependent, creating self-reinforcing configurations that limit analytical diversity and explanatory depth. Supported by chi-square tests, these interactions highlight structural dependencies and misalignments for instance, convenient designs paired with perceptual outcomes explain the study's stable yet narrow conclusions.

Table 9. Research Design and Outcome (n = 150)

Research Design	Purchase Intention	Attitude	Self-Reported Behaviour	Actual Behaviour	Total
Cross-sectional quantitative	82	16	8	2	108
Experimental / quasi-experimental	6	4	2	2	14
Longitudinal quantitative	4	1	1	0	6
Qualitative	5	3	4	0	12
Mixed-methods	4	2	2	2	10
Total	**101**	**26**	**17**	**6**	**150**

Purchase intention overwhelmingly embeds in cross-sectional designs (81% of intention measures), while actual behaviour appears almost exclusively in experimental or mixed approaches. Chi-square test confirms strong association (χ^2 (12) = 28.6, $p < 0.01$, Cramér's V = 0.38 moderate effect). This misalignment is not coincidental: cross-sectional convenience favours intention proxies (easy to measure via surveys), sidelining behavioural realism despite social media's impulse-driven nature. The pattern points to a mechanism where design tractability constrains outcome choice.

Table 10. Sampling Method by Primary Analytical Technique

Sampling Method	SEM (PLS/CB)	Regression	Experimental	Qualitative	Total
Convenience	68	14	4	6	92
Purposive	14	6	4	4	28
Snowball	8	2	0	2	12
Stratified / quota	4	2	2	0	10
Probabilistic	2	2	4	0	8
Total	**96**	**26**	**14**	**12**	**150**

More than 70% of SEM-based analyses rely on convenience sampling, while probabilistic sampling appears more frequently in experimental designs. Chi-square result (χ^2 (4) = 45.2, $p < 0.001$, Cramér's V = 0.55) indicates strong non-random clustering. This dependency suggests a mechanism of "analytical familiarity bias": researchers pair flexible SEM tools with accessible samples to meet publication demands, perpetuating homogeneity even when stronger sampling would better suit causal questions.

Table 11. Data Type by Inferred Decision Outcome

Data Source	Intention-based Claims	Behaviour-based Claims	Total
Self-reported surveys	96	11	107
Experimental data	8	6	14
Qualitative narratives	10	2	12
Platform / behavioural	2	6	8
Secondary / archival	1	0	1
Total	**117**	**25**	**142**

Intention-based claims dominate self-reported surveys (85%), while behaviour-based claims concentrate in experimental or platform-data studies. The asymmetry underscores a perceptual bias: survey logic privileges cognitive proxies, while behavioural evidence requires resource-intensive designs. This reinforces the intention-behaviour gap, with mechanisms tied to data accessibility and common method variance risks (32% of studies per transparency metrics).

These interactions reveal a tightly coupled ecosystem having cross-sectional designs combining with convenience and survey duly applying PLS-SEM considering intention as the dependent variable in most of the cases (55% of studies). The statistical associations and co-occurrences are not artifacts but evidence of methodological path dependence where one choice (e.g., convenience sampling) predictably triggers others (e.g., perceptual outcomes and flexible SEM). This structural interlocking explains the field's convergence and sets up the temporal persistence and realist CMO analyses that follow.

Temporal Trend Analysis (2010–2025)

Despite a nearly threefold increase in publication volume from 2010–2014 (27 studies) to 2020–2025 (68 studies), methodological diversity has not only failed to grow it has remained stubbornly static. This temporal inertia is not a sign of theoretical maturity; it is evidence of entrenched path dependence, where early conventions (convenience, cross-sectional surveys, intention proxies) became self-reinforcing norms that resist change even as the phenomenon evolves rapidly.

Table 12. Research Design by Time Period

Design	2010–2014	2015–2019	2020–2025	Total	% Change (relative share)
Cross-sectional quantitative	18 (67%)	42 (76%)	48 (71%)	108	+4% (stable dominance)
Experimental	2 (7%)	5 (9%)	7 (10%)	14	+3% (marginal)
Longitudinal	1 (4%)	2 (4%)	3 (4%)	6	0% (no growth)
Qualitative	4 (15%)	3 (5%)	5 (7%)	12	–8% (decline)

Mixed-methods	2 (7%)	3 (5%)	5 (7%)	10	0% (static)
Total	27	55	68	150	–

The explosion in output after 2015 reflects growing academic interest in Gen Z and social media, yet the relative distribution of research designs shows virtually no meaningful diversification (chi-square test for temporal shift: χ^2 (8) = 7.4, p = 0.49, non-significant). Cross-sectional quantitative designs have maintained 70–76% share across all periods a troubling sign of methodological lock-in. Longitudinal and mixed methods approach, which could capture the dynamic, iterative nature of platform influence, remain marginal (<10% combined). This is not benign conservatism; it is a failure to adapt methods to a fast-changing phenomenon, likely driven by institutional rewards for quick, low-risk publications over deeper, time-intensive inquiry.

Table 13. Purchase Outcome by Time Period

Outcome	2010–2014	2015–2019	2020–2025	Total	% Change (relative share)
Purchase intention	17 (63%)	36 (65%)	48 (71%)	101	+8% (increasing)
Attitude	5 (19%)	10 (18%)	11 (16%)	26	–3%
Self-reported behaviour	3 (11%)	6 (11%)	8 (12%)	17	+1%
Actual behaviour	2 (7%)	3 (5%)	1 (1%)	6	–6% (declining)

Purchase intention has not just persisted it has strengthened its dominance, rising from 63% to 71% of primary outcomes over time. Actual observed behaviour, already rare, has become even scarcer in recent years (from 7% to 1%). This trend is alarming: as platforms increasingly facilitate impulse buys, algorithmic nudges, and real-time social proof, the field has doubled down on static intention measures rather than evolving toward behavioural evidence. The persistence reflects a deeper problem researchers continue to ask questions that fit existing tools, not questions the phenomenon demands. This methodological inertia risks rendering much of the accumulated knowledge increasingly disconnected from Gen Z's lived consumption reality. The data across 15 years paint a damning picture: explosive growth in volume without corresponding growth in methodological breadth. Proportions of designs and outcomes have remained essentially frozen, suggesting that the field's "progress" is largely additive rather than transformative. This stasis is symptomatic of structural mechanisms (e.g., training in SEM, journal preferences for familiar models, resource barriers to longitudinal work) that lock researchers into proven paths. The lack of diversification over time strengthens the realist argument: dominant configurations are not the best available they are the most institutionally rewarded.

Analytical Synthesis

The coding, cross-tab, and temporal analyses converge on a stark reality: empirical research on social media marketing and Gen Z purchase decisions is not diverse or evolving it is structured around a small number of highly stable methodological configurations. These configurations are not random; they represent a tightly coupled system where design, sampling, data, outcomes, and analysis choices mutually reinforce each other, producing internal consistency at the expense of external validity, behavioural realism, and theoretical progress.

Table 14 consolidates the 150 studies into four dominant configurations, which together account for over 90% of the sample. The percentages are approximate but stable across sensitivity checks.

Table 14: Dominant Methodological Configurations in the Field (n = 150)

Configuration	Core Design	Sampling Strategy	Data Source	Outcome Measure	Analytical Technique	Share of Studies	Key Consequence
C1: Survey–SEM Core	Cross-sectional quantitative	Convenience	Self-reported survey	Purchase intention	PLS-SEM / CB-SEM	55%	Illusion of consensus; perceptual bias
C2: Platform Engagement Model	Cross-sectional quantitative	Purposive	Survey and engagement metrics	Engagement / attitude	Regression / SEM	18%	Contextual surface; still intention-centric

C3: Behavioural–Experimental	Experimental / longitudinal	Controlled / probabilistic	Behavioural / task data	Actual purchase behaviour	Experiments /panel models	9%	Rare but revealing; disrupts dominant claims
C4: Interpretive–Qualitative	Qualitative	Purposive	Interviews / focus groups	Meaning, perception	Thematic analysis	8%	Rich insight; structurally relegated
Residual / mixed forms	Mixed	Mixed	Mixed	Mixed	Mixed	10%	Sporadic, not systemic

Configuration1: The Survey–SEM Core (55%). This is the epicentre showing cross-sectional surveys with convenience samples allowing self-reported intention by analysing through PLS-SEM. Often, researchers repeatedly deploy quick, low-cost designs and flexible modelling tools to produce acceptable results fast. The outcome is a massive body of literature that looks theoretically rich (multiple constructs, mediation paths) but is empirically shallow: intentions are treated as decisions, perceptions as behaviour, student/platform users as representative Gen Z. This is not benign efficiency; it is methodological complacency that has created an echo chamber of consistent but partial findings.

Configuration2: Platform Engagement Model (18%). A superficially more contextual variant: purposive samples of active users on Instagram / TikTok / YouTube, with engagement metrics (likes, shares) layered into survey-based models. While it nods toward platform specificity, it remains trapped in the same intention-centric logic engagement becomes another predictor of attitudes or intentions, not a bridge to actual purchases. This configuration refines the dominant narrative without challenging it, illustrating how incremental tweaks manoeuvre as progress while preserving the core methodological constraints.

Configuration3: Behavioural–Experimental Approaches (9%). These rare studies longitudinal tracking, controlled experiments, or platform transaction data offer the clearest counterevidence to the dominant claims. They frequently show weaker or more variable relationships, higher impulsivity, and lower intention-behaviour translation than survey-based work. Yet their peripheral status reminds that as not rejected rather being subdued. This is not scientific caution it is structural exclusion driven by resource barriers, ethical/ data access issues, and journal preferences for clean, model-driven results.

Configuration4: Interpretive–Qualitative Studies (8%). Qualitative work provides rich, contextual insight into authenticity, influence, scepticism, and pragmatic elements that quantitative models routinely miss. Yet these studies are treated as frontier "colour commentary" rather than foundational input for construct development or model refinement. The separation between interpretive depth and empirical mainstreaming is not accidental; it reflects a broader quantitative bias in the field that privileges generalisable (but narrow) claims over nuanced (but hard-to-scale) understanding.

These four configurations are not isolated clusters; they form a closed methodological ecosystem. C1 dominates because it is tractable and rewarded; C2 refines it without disruption; C3 challenges it but lacks volume; C4 enriches it but lacks integration. The result is a field that has achieved impressive publication volume and apparent theoretical coherence while remaining strikingly narrow in epistemological scope. Growth has been additive, not transformative.

The crux is that what the studies reveal about Gen Z purchase decisions are cocooned to methodological pigeonholes where they were observed. The configurations do not represent the best available science they represent the most feasible discipline under current institutional conditions.

Methodological Implications and Research Agenda

The foregoing analyses reveal a literature that has expanded in scale yet remained largely static in its methodological pursuit. Despite the growing complexity of Gen Z's digital consumption, research practices continue to tap convenience-driven designs, perceptual proxies, and familiar analytical approaches. As a result, much of what we know rests on simplified representations that struggle to capture behavioural realism, temporal dynamics, or the diversity of pathways through which Gen Z engages with social media. This pattern is not a sudden development as observed (Aguinis, Ramani, & Alabduljader, 2018). These studies further caution on the methodological homogeneity that can be misleading towards theoretical maturity and even may diminish the domains explanatory power. In this context, the continued reliance on the SEM as a core analytical tool, risks producing findings that are increasingly polished yet progressively detached from the impulsive, algorithm-mediated social-media oriented buying behaviour (Sheeran, 2002); (Armitage & Conner, 2001).

Breaking this loop requires deliberate and coordinated change, guided by the mechanisms surfaced through the realist synthesis. Journals and editors occupy a pivotal position in this transformation. As Hulland, et.al (Hulland, Baumgartner, & Smith, 2018) argue in their critique of routine PLS-SEM usage, editorial incentives can either reinforce methodological inertia or actively challenge it. Purposeful calls for longitudinal, mixed-method, or behaviourally anchored studies of Gen Z, coupled with reviewer expectations that reward genuine innovation such as platform data integration or field-based experimentation would signal that methodological ambition, not just statistical sophistication, is valued. Devoid of such signals, the familiar pressures of publish-or-perish will continue to steer researchers toward speed and safety rather than substantive insight (Banks, et al., 2016).

Equally important is reform at the level of scholarly training. Doctoral programmes and advanced methods workshops must move beyond treating SEM as a default terminal and instead cultivate fluency in behavioural and hybrid approaches. Exposure to tools such as transaction-level data, digital trace analysis, or eye-tracking alongside qualitative designs that help counter common method variance (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003) would equip emerging scholars to engage Gen Z's digital behaviours more directly. Funding bodies, too, have a role to play by prioritising proposals that combine perceptual and observed measures, anchoring (Eisend, 2015) call for methodological pluralism in advertising research. Investment in shared, anonymised repositories of Gen Z behavioural data would further lower entry barriers and encourage experimentation beyond survey-based paradigms.

At a conceptual level, this review underscores the need to rethink the privileged status of intention. For too long, intention has served as the focal outcome, even when the empirical setting is characterised by frictionless transitions from exposure to action. Repositioning intention as a precursor rather than a proxy for behaviour opens space for hybrid designs that link self-reports with real-time outcomes, such as click-through paths, purchase logs, or voucher redemptions. Such architectures can more effectively trace the 'exposure–engagement–behaviour' sequence central to digital consumption, as anticipated in Brodie et al. engagement model (Brodie, Ilic, Juric, & Hollebeek, 2013). Longitudinal, multi-platform diaries and co-created measurement instruments that incorporate Gen Z perspectives can further surface subtle influences such as algorithmic amplification or perceived authenticity that are often flattened in conventional scales (Sokolova & Kefi, 2020).

Finally, methodological renewal must be accompanied by greater reflexivity. Periodic meta-audits conducted every five to seven years could prompt scholars to justify their design choices explicitly, interrogate the suitability of static models in rapidly evolving digital environments, and confront limitations related to bias and generalisability. Such practices align with (Shadish, Cook, & Campbell, 2002) guidance on strengthening validity and would help prevent methodological habits from hardening into unexamined norms. While these reforms demand effort, the cost of inaction is higher: a body of knowledge increasingly misaligned with the succumbed digital realities of Gen Z.

This review does not call for the abandonment of existing methods, but for their transcendence. What researchers choose to measure ultimately shapes what they come to understand. The methodological monoculture documented here has delivered internal coherence, but often at the expense of completeness and behavioural fidelity. Looking ahead, incremental adjustments within established templates are unlikely to suffice. The next phase of research is expected to embrace pluralism, prioritise behavioural grounding, and institutionalise reflexive scrutiny thereby ensuring the research on Gen Z and social media remains theoretically meaningful, empirically credible, and responsive to the ongoing evolution of digital consumer.

Discussion: What Gets Measured Shapes What We Know

This review set out to reflect on a basic but often overlooked tenets in research on social media marketing and Gen Z consumption: whether the conclusions that dominate the field are primarily driven by consumer behaviour itself (as tested and observed) or by the ways researchers have chosen (skewed) to study it. The answer suggested by the evidence is clear. What the literature tells us about Gen Z purchasing is closely tied to a limited set of recurring research practices, and those practices have quietly shaped both the questions that are asked and the answers that appear most often.

Across fifteen years of research, studies have repeatedly relied on similar designs, samples, outcome measures, and analytical tools. Surveys administered at a single point in time, typically to easily accessible respondents, have become the default approach. Purchasing is usually inferred from stated intentions rather than observed actions, and complex statistical models are frequently applied to self-reported data. While these choices are individually defensible, their repeated combination has produced a body of evidence that is internally consistent but methodologically narrow. Notably, this pattern has remained stable even as interest in the topic has grown rapidly, suggesting that expansion has occurred within an established template rather than through experimentation with alternative approaches.

This methodological concentration has important implications for what the field has come to regard as settled knowledge. The literature consistently reports positive relationships between social media marketing variables such as influencer characteristics, engagement, or trust and Gen Z purchase intentions. These findings are robust within the contexts in which they are generated. However, they largely reflect how young consumers *say* they respond to marketing, not how they actually behave in fast-moving, algorithmically curated digital environments. Social media platforms are designed to prompt spontaneous, situational, and socially embedded decisions, yet these dynamics are rarely captured when behaviour is reduced to static self-reports. When studies do move closer to observing behaviour directly, the effects of marketing inputs tend to be less uniform and less predictable, pointing to a more contingent reality than the dominant narrative suggests.

Rather than viewing this pattern as a series of isolated methodological shortcomings, it is more useful to understand it as the outcome of structural conditions within academic research. Time pressures, resource constraints, and strong incentives to publish in recognised outlets encourage approaches that are efficient, familiar, and easily evaluated by reviewers. Over time, certain ways of studying Gen Z consumption have become normalised as credible and publishable, making it increasingly difficult for alternative designs to gain traction. As a result, continuity is rewarded more than experimentation, and methodological choices are reproduced even as the platforms and behaviours under study continue to change.

The consequences of this situation extend beyond academic debate. For practitioners, the literature may convey a sense of stability and control that does not fully reflect the volatility of real-world social media influence. For policymakers and consumer advocates, the emphasis on intentions rather than behaviour limits the usefulness of research in addressing issues such as impulsive buying, exposure to manipulative content, or the role of platform architecture in shaping consumption. At the disciplinary level, the repeated refinement of similar models, risks slowing theoretical development by focusing attention on incremental variation rather than on deeper questions about how digital consumption should be conceptualised and studied.

Overall, the review suggests that the field has produced a coherent but partial understanding of Gen Z purchasing in social media contexts. What is known is strongly shaped by what is easiest to measure, rather than by the full range of processes through which influence operates in everyday digital life. This does not invalidate existing findings, but it does place clear limits on how far they can be generalised. Addressing these limits requires more than adding new variables to established models; it calls for deliberate methodological diversification that better reflects the temporal, behavioural, and contextual realities of contemporary consumption. The following research agenda outlines concrete ways in which such a shift might be achieved.

CONCLUSION

This review highlights that methodological choices play an active role in shaping what is known about social media marketing and Gen Z purchase behaviour. Much of the existing evidence reflects insights generated within a limited set of commonly used research approaches, rather than the full range of ways in which social media influence operates in everyday consumption.

Acknowledging this boundary is not a critique of past research, but a necessary step toward strengthening future work. Expanding methodological approaches and paying closer attention to behavioural and contextual dynamics can help the field move toward findings that are not only consistent, but also more representative of contemporary digital consumption. Ultimately, how Gen Z purchasing is studied will continue to influence how it is understood, and meaningful progress depends on a willingness to study it differently.

Future Research Agenda

This review shifts the focus from individual methodological choices to the recurring ways research on social media and consumer behaviour has been carried out over time. By stepping back from specific techniques and looking at the field as a whole, it helps explain why certain types of findings appear so frequently, while others remain rare.

Future research needs to be guided more carefully by the questions it seeks to answer. Studies of social media influence will gain depth when data, methods, and analyses are chosen to reflect how consumption actually unfolds in digital settings. Progress in this area is unlikely to come from further elaboration of familiar models alone, but from exploring a wider set of ways to study consumer behaviour as platforms, practices, and contexts continue to change.

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