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Exploring Overlooked Features of Online Touchpoints in Multitouch Attribution Models: A Qualitative Study

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Abstract

The challenge of allocating marketing budgets across multiple online channels is a significant issue for practitioners and continues to be a compelling area of research within the academic community. Many practitioners attribute credit to touchpoints in analyzing online users' journeys based on intuition or by comparing existing models. Touchpoints are the interaction moments between companies and customers. Marketers monitor all data related to touchpoints throughout the customer journey and attempt to assess the impact of each advertising channel. Understanding each touchpoint is crucial for making decisions about budget allocations and setting inventory prices. Numerous studies have been conducted to categorize and analyze touchpoints. However, a detailed and comprehensive study on this topic is lacking. In this study, nine semi-structured interviews were conducted with experts and academics in the field, leading to the identification of 35 distinct touchpoint features. The features were extracted using MAXQDA software and a thematic analysis methodology. These features have been organized into five main categories: Time (9 features), Technology (6 features), Marketing (7 features), Visits (7 features), and Events (6 features). Utilizing

these features allows for detailed monitoring of online user behavior, and by integrating them into attribution models, it becomes possible to make accurate predictions about conversions.

Keywords: Online touchpoints, Multitouch attribution models, Digital marketing, Online customer journey

Introduction

Technological advances are giving both marketers and customers a pool of data that can be analyzed for various purposes. Nowadays, these data reveal that customer behavior in searching for information, evaluating products/services, making purchasing decisions, and sharing experiences has changed radically (Schweidel et al., 2022). By 2026, the number of online shoppers is expected to reach 2.86 billion, highlighting the surge in e-commerce fueled by greater internet penetration and increased convenience. As of 2025, there are approximately 28 million e-commerce sites globally, representing a 2.9% increase from the previous year (Commerce, 2025).

To provide better customer experience and to understand customer behavior throughout the online journey, it is important to recognize which channels customers prefer, how these channels are interconnected, and how they impact customers' buying decisions (Becker et al., 2017). Madhavaram and Frow (2017) proposed that managing customer interactions with a company strategically contributes to a superior customer experience. This involves creating positive perceptions and fostering a willingness in customers to favor a product or service, aiming for long-term benefits. Gentile et al. (2007) further elaborated that customer experience stems from interactions that trigger reactions, which vary greatly across different companies, individuals, and industries.

Throughout their journey in the online environment, customers engage in various interactions with a brand or company across different channels, such as websites, social media, or e-commerce platforms, referred to as touchpoints. Becker and Rech (2024) mention the crucial role touchpoints play in shaping customer experience and perceptions along the customer journey. Touchpoints provoke a reaction and involvement at different stages of the customer journey. These engagements may be rooted in multiple levels—rational, emotional, sensory, physical, and spiritual—and their impact is measured against customer expectations and the company's touchpoint quality (Shaw & Ivens, 2002).

Research on customer journey analysis can be divided into two primary strands. The first addresses the experiences customers have at individual touchpoints, examining how these interactions shape perceptions and influence beliefs about a brand's attractiveness and performance (Kaur & Gupta, 2020; Kincl & Štrach, 2010; Tueanrat et al., 2021). The second focuses on the role of touchpoints in influencing purchasing behaviors across the customer journey. This includes identifying key touchpoints, or "moments of truth" (Lemon & Verhoef,

2016) and using attribution models to assess the impact of each touchpoint and their combined effect in multi-touchpoint environments (Anderl et al., 2016b; Becker et al., 2017; De Haan et al., 2016).

These attribution models rely on data to gauge touchpoint performance and their positional influence in the journey, but they do not account for the perceived quality of individual touchpoint features (Klapdor et al., 2015; Anderl et al., 2016b; Dinner et al., 2014). Attribution models have been developed to assign conversion credits across various touchpoints along the customer journey. These models, which are based on either linear or dynamic allocation rules, aim to quantify the influence each touchpoint has on the conversion process. They utilize various algorithms and mathematical approaches to optimize credit allocation. Much of the existing research on multi-touch attribution has focused on exploring different algorithms and mathematical modeling techniques (e.g., Shao & Li, 2011; Zhang et al., 2014), while relatively little attention has been given to the touchpoints themselves.

Specifically, a comprehensive and systematic examination of the features of individual touchpoints is lacking. Therefore, this research concentrates on identifying and structuring the features of individual marketing touchpoints within the online customer journey. This research is guided by the following primary research question: Which features of individual marketing touchpoints can be systematically identified to support the development of multi-touch attribution models?

Literature Review

In today's era of digitalization, online presence is crucial for businesses to survive. This means they need robust digital advertising strategies to captivate and engage their audiences. With the variety of online advertising methods available, businesses allocate significant budgets to drive website traffic through various channels. Banners and pop-ups are examples of this broad landscape of digital advertising (Pattanayak et al., 2022). This need necessitates data-driven advertising methods so that businesses can tailor messages to reach customers effectively across the right channels at optimal times.

As a major challenge for businesses, it is not always clear which channel contributes most to Return on Ad Spend (ROAS). This uncertainty can lead to difficulties in measuring the performance of each channel. Algorithmic approaches, which include statistical modeling and machine learning, help evaluate advertising effectiveness, aiding forecasting and optimizing spending. As a measurement technique, multi-touch attribution models (MTAMs) assess advertising performance by considering all customer journey touchpoints and assigning proportional credit to those touchpoints. This enables marketers to measure each channel's impact on conversions.

The term "digital advertising campaign" refers to a sequence of coordinated advertisements unified by a single idea or theme to target a specific audience. By using different media channels, the goal of these campaigns is to promote a product or service while encouraging internet users to discover the brand. Through this approach, companies can fulfill their campaign goals and engage their target audiences with the campaign's core message (Mrad & Hnich, 2024).

Channels are defined as the media used by marketers to deliver advertisements. Channels serve as the medium for contact between the firm and the customer (Neslin et al., 2006). These moments of interaction are called touchpoints. Marketers use different channels to deliver their messages and meet campaign objectives, ranging from traditional outlets like TV and radio to digital platforms such as social media, search engine advertising, display ads, and email.

Touchpoints are the various actions and interactions that occur as a user navigates through the customer journey. These touchpoints encompass every engagement a user has with a brand, from initial contact to post-purchase experiences. Each touchpoint contributes to conversion. The term conversion refers to the point at which a visitor to a website becomes a customer or potential customer (Matoulek, 2018). Depending on the campaign objectives defined by brands, conversion actions could include making a purchase, signing up for a newsletter, subscribing, downloading an app, or simply visiting a webpage.

An example of a typical customer journey, as shown in Figure 1, may consist of numerous touchpoints. These touchpoints can be impressions or clicks. The customer might engage with multiple touchpoints—beginning with a social media ad, followed by a paid search ad, and then an email campaign—before ultimately visiting the website and completing a purchase. Faced with all these touchpoints, marketers must determine which one contributed most significantly to the conversion.

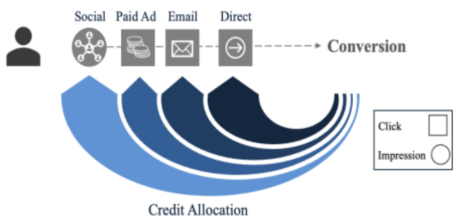

Figure 1.Credit allocation in the online customer journey

To allocate conversion credits to touchpoints, attribution models were introduced. Attribution models are considered one of the most popular marketing approaches used by marketers (Mrad & Hnich, 2024). By measuring the effectiveness of each marketing channel in achieving the desired outcome, marketers can pinpoint the most successful sources of conversions. This insight allows them to optimize their marketing strategies for better results.

There are different classifications of these models. Some classify them as single-touch and multi-touch attribution models (Mrad & Hnich, 2024), while others categorize them as static and dynamic attribution models (Anderl et al., 2016a; Li & Kannan, 2014; Shao & Li, 2011). Jayawardane et al. (2015) classified attribution models into three categories: simplistic models, rule-based models, and algorithmic models.

In single-touch attribution models, the entire credit (100%) is assigned to one touchpoint in the channel that leads to conversion. These models were the earliest presented in this field (Shao & Li, 2011). The last-touch model assigns credit to the last touchpoint of the customer journey. This means only the final channel the customer interacted with before converting is considered in evaluating marketing effectiveness. The first-touch model uses the same mechanism but assigns all credit (100%) to the first touchpoint in the initial channel visited. The underlying idea is to emphasize the importance of the first channel through which a customer discovers the brand.

These models are easy to implement and understand; for this reason, they remain among the most widely used methods (Shang, 2023). However, their main drawback is that they do not account for all touchpoints along the customer journey, often overlooking the influence of intermediate interactions. Therefore, researchers developed a more comprehensive approach known as multi-touch attribution models (MTAMs), which provide a more nuanced understanding of how various touchpoints contribute to conversions (Shao & Li, 2011).

The linear attribution model, also known as even weighting, is the simplest among MTAMs. This model divides credit equally among all channels, reflecting the assumption that each touchpoint contributes similarly to the outcome (Matoulek, 2018). The time-decay model assigns more credit to touchpoints closer to conversion, valuing more recent interactions. The U-shaped model prioritizes the first and last touchpoints, highlighting their crucial roles in brand discovery and final conversion.

Despite the simplicity of these models, they often lack accuracy because they do not consider actual user data, leading to static credit allocation regardless of varied customer paths. This limitation spurred the development of data-driven models, which create more dynamic and tailored attribution methods by predicting credit allocation based on historical data and real user interactions (Gupta et al., 2020; Machado & Karray, 2022; Miralles-Pechuán et al., 2020). In contrast to heuristic models, the allocation of credit in these models is not static; algorithms dynamically adjust the values, allowing for more accurate attribution.

Therefore, a new generation of customized attribution models has emerged. Table 1 outlines several studies related to multi-touch attribution models (MTAMs), highlighting their various approaches. It is important to acknowledge that no model is flawless, and each carries distinct advantages and limitations (Fernández, 2020).

Table 1.Literature review (methodologies of attribution models)

Study	Methodology	Description
Manchanda et al. (2006)	Survival model	This study investigates the impact of banner advertising on online users' purchasing behavior. The findings indicate that increased advertising exposure, number of website visits, and pages viewed have a positive effect on repeated purchases. On the other hand, the diversity of creative content negatively affects these probabilities.
Shao & Li (2011)	Bagged logistic regression	Using methodologies to estimate the individual advertising channel contributions and to quantify the attribution of various advertising channels. Applying their models to a real-world dataset from a multichannel campaign, the authors find consistent results that validate the effectiveness of their methods.
Li & Kannan (2014)	Hierarchical Bayesian (purchase decision hierarchy framework)	The authors introduced a measurement model designed to analyze three key aspects of online user touchpoints with channels: 1) online channel consideration, 2) visits through these channels over time, and 3) the subsequent purchases made on the website. The model attributes conversion credit to channels, revealing that the relative contributions of these channels differ significantly from those indicated by currently used metrics. Their model helps to estimate the carryover and spillover effects of previous touchpoints at both the visit and purchase stage.
Anderl et al. (2016a)	Markov chain model	The authors introduced an attribution framework that models customer paths as sequences of first- and higher-order Markov walks. The findings indicate marked deviations from commonly used heuristics like the last-click attribution model. Additionally, the study uncovers unique channel preferences (carryover effects) and interaction effects both within and across different channel categories (spillover effects).
Abhishek et al. (2012)	Hidden Markov Model (HMM)	By employing an HMM, their analysis revealed that different advertising formats, such as display and search ads, impact consumers differently depending on their current stage in the decision-making process. Their results show that display ads typically influence consumer engagement at the early stages, while in contrast, search ads exert a significant influence throughout the user’s decision process.
Xu et al. (2014)	Mutually exciting point process	The focus of this study is particularly on the dynamic interactions between advertisement clicks and the impact of clicks on purchase conversion. The results show that while some ad clicks might not directly lead to purchase, they can trigger subsequent clicks on other ads that do result in sales. Their model treats ad clicks and purchases as interdependent random events that occur in continuous time.
Zhang et al. (2014)	Additive hazards Survival theory	They introduced a data-driven attribution model that offers a distinct advantage by eliminating the presentation biases that are inherent in most other attribution models. One of the core capabilities of our model is its ability to predict the probability of a user’s conversion.
Ren et al. (2018)	Dual attention Recurrent Neural Network	Their model directly learns attribution values from the goal of estimating conversions. The model uses a sequence-to-sequence approach for predicting user clicks, combining both post-view and post-click attribution patterns. These points refine the overall conversion estimation.
Yang et al. (2020)	Deep learning model (DeepMTA)	Their model has two main components: 1) a conversion prediction model that utilizes phased Long Short-Term Memory (LSTM) networks to accommodate varying time intervals, and 2) an additive feature attribution model that incorporates Shapley values to assign credit to different advertising touchpoints. Their model focuses on three aspects of customer journey: 1) the sequence order of events, 2) the frequency of events, and 3) the significance of influence of recent interaction also known as time-decay effect.
Samuel van Tol (2024)	supervised machine learning model (LSTM)	The author has assessed the efficacy of heuristic and data-driven models in analyzing customer journeys, using real-world e-commerce data. Among the heuristic models, time-decay model emerged as the most effective. Time-decay model has shown the highest conversion rates. Among data-driven models, the bagged logistic regression model founded to be the least effective. Also, the fine-tuned random forest model ranked among top performers. The fine-tuned random forest model showed robust capability in attributing conversions accurately. The author uses LSTM architecture to perform the analysis. LSTM model can remember and process sequence of data over long periods.

While many studies have concentrated on the algorithms and models used for attribution, the focus of this study is to explore which features of touchpoints affect these models and to identify key indicators for evaluating touchpoints. This will help in adjusting the model to better fit the specifics of the customer journey. In e-commerce, touchpoints act as software-based interactions, while channels represent hardware solutions (Wagner et al., 2018). This distinction highlights the need for algorithms that can utilize detailed touchpoint data to improve attribution accuracy and increase conversion probabilities. Complex attribution models might not always be necessary, as simpler heuristic approaches can effectively enhance budget allocation (Li et al., 2016).

In this study, we have sought to identify the features of touchpoints by reviewing academic literature and conducting expert interviews. Nowadays, advertisers and marketers are using real-time bidding for online ads (Cai et al., 2017); this increases the importance of accurate measurement of digital touchpoints to precisely gauge their influence on customer journeys. These touchpoints critically shape the consumer decision-making process and enhance the overall customer experience (Santos & Gonçalves, 2021). As digital touchpoints increase, they enable consumers to make more informed decisions (Batra & Keller, 2016). However, ensuring a seamless transition between these touchpoints remains a challenge for businesses (Verhoef et al., 2015). This fluidity between touchpoints is essential for delivering a strong customer experience.

Schmidt and Eisend (2015) conducted a meta-analysis on effective advertising frequency, showing how frequency impacts advertising outcomes. The results of their study indicated that in an experimental setup, optimum attitude toward a subject is achieved after about ten exposures, while recall continues to increase linearly and does not level off before the eighth exposure. Gao and Qiao (2025) studied reach measurement, optimization, and frequency capping under the effects of privacy concerns. They examined a pivotal technology called frequency capping, which allows marketers to control how many times a specific user sees an advertisement. Results indicated a slight decline in ad performance with increased privacy, yet the cost to platforms remained minimal.

With the introduction of privacy and tracking policies (e.g., consent options for cookies), it is crucial to target online users more accurately. Marketers can now allocate better conversion credits, optimizing their return on ad spending (ROAS). Leguina et al. (2021) developed a robust and reliable methodology to determine the optimal number of ad exposures for different online users to maximize ROAS. When touchpoints with users vary in number and type, it becomes critical to deeply understand the characteristics and impacts of each touchpoint. This understanding can significantly enhance the effectiveness of targeted marketing strategies.

Lemon and Verhoef (2016) and Cambra-Fierro et al. (2017) categorized touchpoints between customers and firms based on who initiates or controls the encounter. Rosenbaum et al. (2017) pointed out that managers often wrongly assume all organizational touchpoints are equally important to consumers. Research by Sands et al. (2016) shows that the value and importance of touchpoints vary throughout the decision-making process, affecting consumers' emotional responses concept referred to as touchpoint positivity by Baxendale et al. (2015).

Notably, consumer priorities and behaviors have shifted due to the pandemic, affecting online purchasing behavior and responses to marketing strategies such as email marketing, as well as increasing tolerance for variability in inventory and shipping delays (Santos & Gonçalves, 2021; Swinscoe, 2020). Batra and Keller (2016) argue that the most value is derived by integrating these touchpoints throughout the decision journey, with each stage addressing the consumer's specific informational needs.

Hallikainen et al. (2018) studied 2,348 individuals' preferences for digital touchpoints and identified four distinct segments: anti-digital, anti-social, majority, and digital channel enthusiasts. Their analysis highlighted differences in technology readiness, internet use, and demographics. It was found that functional touchpoints like email, websites, and search engines are favored across all segments, indicating a general preference for these more traditional digital platforms.

Straker et al. (2015) examined digital touchpoints across 16 industries, identifying 34 types and grouping them into four typologies. Key findings showed the most-used touchpoints were websites, Twitter (now X), Facebook, YouTube, and LinkedIn. Other significant digital touchpoints include contact emails, Google+ accounts, and mobile apps. The study revealed no significant correlations between a company's age, size, or location, although this landscape may evolve as new touchpoints emerge.

Despite the established concepts regarding touchpoints, empirical data on the features of touchpoints, especially in newer digital media, remains limited. Table 2 offers a summarized overview of research on touchpoint classifications and their associated channels.

Table 2.Summary of empirical research on touchpoints typology

Study	Approach	Channel	Description
Anderl et al., (2016b); De Haan et al., (2016)	Origin of contact	Online and/or offline	- Touchpoints between a firm and its consumers can be either firm-initiated or consumer-initiated. *Firm-initiated* touchpoints occur at the company's discretion, such as display advertising, where the firm decides the timing and frequency. *Consumer-initiated* touchpoints are activated by potential consumers through their actions, such as performing active searches on price comparison websites.
	Degree of personalization	Online and/or offline	- Advertising message personalization varies in levels. A *high level* of personalization targets specific individuals by focusing on unique attributes, making the message highly tailored. On the other hand, a *low level* of personalization is designed to reach a broad, general audience without specific targeting.

	Degree of content integration	Online and/or offline	- The degree of integration with an editorial network can vary. *Content-integrated* touchpoints are those where the content is seamlessly integrated within the broader media and editorial framework. In contrast, *Content-Separate* touchpoints maintain minimal or no connection with the editorial network, standing apart from the main media content.
Anderl et al., (2016b)	Brand keyword usage	Online	- In search behavior, there are two main types of keyword usage: *Branded Keywords*, where consumers search using a specific brand or retailer's name, typically seen in branded searches, and *Generic Keywords*, where searches are broad and non-specific, often used on price comparison or review sites.
Lemon and Verhoef, (2016); Baxendale et al., (2015)	Ownership	Online and/or offline	- Control over a touchpoint can be categorized into three types: *Brand-Owned*, where the brand manages its touchpoints like websites or loyalty programs; *Partner-Owned*, where control is shared with partners, seen on platforms like affiliate websites; and *Customer-Owned* or *External*, where touchpoints are managed by customers or independent entities, such as social media and review sites.
Anderl et al., (2016b)	Browsing goal	Online	- Touchpoints can be categorized based on the purpose of browsing: *Informational Search Goals* touchpoints are those where consumers visit websites to gain knowledge, while *Navigational Search Goals* touchpoints are those where the intent is to directly reach specific websites.
Straker et al. (2015)	Industry	Online	- *Functional Touchpoints*, like websites and emails, mainly facilitate one-way communication and are essential for initial contact and ongoing interaction, such as subscription services and customer notifications. *Social Touchpoints* offer two-way interaction, allowing for real-time engagement and feedback across various social media platforms. *Community Touchpoints* foster engagement through interactive platforms like YouTube and blogs. Lastly, *Corporate Touchpoints* are informational, supporting other touchpoints by providing detailed company information and handling customer feedback through digital forms and e-commerce platforms.

Despite extensive research on algorithms for more efficient attribution, there remains a gap in understanding how touchpoint features themselves can enhance attribution model performance. Effectively managing various touchpoints is crucial for maintaining a seamless customer experience, which should be a top priority for any company. Businesses need to ensure consistency across all touchpoints to sustain customer engagement and drive momentum (Madhavi & Frow, 2017). By understanding the features and effectiveness of these touchpoints throughout the customer journey in e-commerce, businesses can allocate resources more efficiently. To address this research gap, this study incorporates both a comprehensive review of existing literature and expert interviews, integrating academic perspectives with practical insights to explore opportunities for improving future attribution model performance

Methodology

The employed methodology demonstrates the reliability and validity of the scientific findings. It is crucial to consider the research's goal, nature, subjects, and practical constraints when choosing a methodology. The chosen approach should be tailored to the study's specific needs and objectives. As emphasized by Johnson and Clark (2006), business and management researchers must be aware of the philosophical choices they make when selecting research strategies, as these decisions significantly affect both how studies are conducted and how their results are interpreted.

This study employs an abductive approach, a methodology premised on reasoning that bridges inductive and deductive logic (Sanders, 2016). Charles Sanders Peirce (1878–1958) introduced abduction as a third principle of reasoning, which helps resolve conflicts between induction and deduction. This approach allows for the adaptation and refinement of established theories, giving researchers the opportunity to integrate new insights from less explored areas of study.

The abductive approach blends inductive and deductive reasoning, enabling researchers to use creativity and systematic inquiry in their investigations (Flick, 2018). Semi-structured and in-depth (unstructured) interviews are regarded as non-standardized methodologies and are predominantly situated within the domain of qualitative research (King et al., 2018).

In this study, semi-structured interviews were used as the primary data collection framework. While key themes and prospective questions were pre-established, the interview process allowed for flexibility and dynamic progression. As such, supplementary questions were incorporated to explore the research objectives more deeply. These methods allowed participants to freely express their thoughts and personal experiences.

Ultimately, experts who were willing and available to participate were interviewed. Prior to the interviews, experts validated the questions and interview protocol, which were designed in alignment with the study's research objectives. For this study, in order to be qualified as an expert, interviewees had to meet the following criteria:

A minimum of four years of significant professional experience within their respective domain.

- Extensive technical proficiency and strategic insight in the field of marketing.

- Specialized expertise in attribution models or a closely allied area of study.

Table 3 presents the characteristics of the interviewees in this study. Qualitative studies typically target a small group, focusing intently to achieve a thorough understanding and exploration of the phenomenon (Maxwell & Miller, 2008).

Table 3. Profile of interviewees

Interviewee	Name	Gender	Expertise related to research	country
Int. 01	Russel	Male	CEO and Co-Founder of attribution modeling company	United Kingdom
Int. 02	Melanie	Female	CEO and Co-Founder of an attribution modeling company	Germany
Int. 03	Simin	Female	Digital marketing and performance marketing specialist	Iran
Int. 04	Marzieh	Female	Senior performance marketing specialist	Iran
Int. 05	Mohammad	Male	PPC advertising specialist	Iran
Int. 06	Mostafa	Male	Researcher and university lecturer in marketing	Iran
Int. 07	Amirhossein	Male	Digital marketing manager	Iran
Int. 08	Tamanna	Female	Marketing communications consultant	Iran
Int. 09	Sajad	Male	Performance marketing strategies and Google Ads lecturer	Iran

In this type of research, achieving data saturation is critical. In the present study, data saturation was reached after nine interviews. All interviews were conducted online. With the consent of the interviewees, conversations were recorded. Additionally, manual notetaking was performed.

To derive indicators related to the research topic and integrate them with indicators extracted from the literature, thematic analysis and thematic network analysis were applied. Thematic analysis is a method used for identifying, analyzing, and reporting patterns within qualitative data. This approach provides a systematic framework for analyzing textual data, transforming disparate and diverse information into rich, detailed insights (Braun & Clarke, 2006). Thematic analysis seeks to extract prominent themes from a text at various levels.

Moreover, thematic network analysis facilitates the organization and visualization of these themes. In other words, thematic analysis helps to identify and explain the “what” and “why” of a phenomenon, while thematic network analysis focuses on the “how.” Thematic networks systematically organize themes into: (a) Basic themes, which consist of key codes and specific points in the text; (b) Organizing themes, which are categories formed by grouping and summarizing basic themes; and (c) Global themes, which are overarching concepts representing the governing principles of the text as a whole.

Thematic analysis consists of six systematic stages. The first stage involves repeatedly reviewing the text to gain a thorough understanding of the data. Accordingly, after the interviews, the researchers read the extracted transcripts multiple times and recorded initial observations. This stage, known as familiarization with the data, establishes the foundation for analysis.

In the second stage, data relevant to each code are collected. Basic codes are generated, yielding primary ideas. A systematic analysis ensures that all data items are given equal and comprehensive attention.

In the third stage, the focus shifts to a broader level, where various codes are grouped to form potential themes. The fourth stage involves reviewing and refining these themes. At this point, the researcher determines whether the potential themes genuinely qualify as distinct themes; some may be merged, discarded, or subdivided.

In the fifth stage, themes are defined and labeled in accordance with the research objectives and existing literature. Finally, in the sixth stage, the finalized themes are documented and articulated (Braun & Clarke, 2006). In this research, data analysis was conducted using MAXQDA software.

Results

After a thorough and repeated review of interviews, the data extracted from interviews were analyzed and coded using MAXQDA software. The themes are presented as nodes in a web-like diagram. This network visually maps relationships between themes in a non-hierarchical structure, helping to understand data through layers of basic, organizing, and global themes. Through this process, characteristics of touchpoints were identified, and similar codes were grouped, resulting in the emergence of sub-themes. In total, 35 themes were identified, which were categorized into three global themes and five organizing themes. Global themes consist of behavioral concepts, Marketing influence, and Technology profile. Behavioral concepts include three organizing themes: Time, Visits, and Events. Marketing influence consists of Marketing theme, and Technology profile consists of Technology theme. Table 4 presents the results of the analysis, showing that the organizing theme category encompasses several basic themes, where these basic themes may include different variables. Also, in Table 4, the repetition of a theme by interviewees is recognized. As expected, the more significant features of touchpoints were mentioned more frequently.

Table 4.Results, organizing themes, and basic themes

<table>
<tr><th>Global theme</th><th>Organizing theme</th><th>Basic theme</th><th>Variables mentioned</th><th>Repetition of the theme</th></tr>
<tr><td rowspan="11">Behavioral concepts</td><td rowspan="9">Time</td><td>Time of the day</td><td>Hours</td><td>7</td></tr>
<tr><td>Day of the week</td><td>Saturday, Sunday, Monday, Tuesday, Wednesday, Thursday, Friday</td><td>4</td></tr>
<tr><td>Month</td><td>January, February, March, April, May, June, July, August, September, October, November, December</td><td>3</td></tr>
<tr><td>Season</td><td>Spring, Summer, Autumn, Winter</td><td>3</td></tr>
<tr><td>Year</td><td>-</td><td>2</td></tr>
<tr><td>Holidays (public or widely known holidays)</td><td>-</td><td>4</td></tr>
<tr><td>Time elapsed since first visit</td><td>-</td><td>7</td></tr>
<tr><td>Time elapsed since previous visit</td><td>-</td><td>5</td></tr>
<tr><td>Days from conversion</td><td>-</td><td>4</td></tr>
<tr><td rowspan="2">Visits</td><td>Page view</td><td>count</td><td>4</td></tr>
<tr><td>Engagement Depth</td><td>scroll_depth, clicks_within_a_page, video_watch_time</td><td>4</td></tr>
</table>

		Landing/Exit page	Home_page, Product_page, Category_page, Search_result_page, Check_out_page, Cart_page, Blog_content_page, Account_page, othe_page	3
		Session duration	-	6
		Bounce rate	-	3
		Visitor Status	new_visitor, returning_visitor, loyalist	8
		Frequency of visits	-	9
	Events	Micro_conversions	Newsletter_signup, Account_creation, social_like, sicoal_comment, social_share	4
		View	view_item, view_item_list, time_spend_in_multimedia_content	4
		Select	select_item	5
		Basket	add_to_wishlist, add_to_basket, remove_from_basket, view_basket	5
		Card	add_payment_info, add_shipping_info, card_abandonment	5
		Purchase	-	9
Technology profile	Technology	Browser type	Google Chrome, Mozilla Firefox, Apple Safari, Microsoft Edge, Internet Explorer, Opera, Samsung Internet, other	3
		Browser version	Latest, Recent, Outdated	2
		Operating system	Windows, macOS, Android, iOS, iPadOS, Linux, Chrome OS, KaiOS, other	1
		Device type	Mobile, Desktop, Tablet	4
		IP address location	-	3
		Language	-	2
Marketing influence	Marketing	Channel type	Organic_search, Paid_search, Social_media, Email, Dispaly_ads, Affiliate, Content_marketing, Refferal, Video_marketing, Mobile_app, Direct_visit	9
		Campaign medium	TextAd, Display, Email, Referral, Social, Banner	6
		Campaign purpose	Awareness, Engagement, Consideration, Conversion, Lead_generation, Retention, Education, Traffic, Upsell_Crosssell	9
		Position in Journey (Funnel)	First Interaction (awareness), middle interactions (consideration), Last interaction (conversion)	6
		Message Type	Informational (blog post), promotional (discount offer), emotional (storytelling ad)	5
		Keywords	-	7
		Demographics	Age, Gender	2

The interviewees affirmed that the features listed in Table 4 as basic themes represent key characteristics of touchpoints that are important to incorporate into multi-touch attribution models. Incorporating these identified features can support the development of more effective models, thereby enhancing the likelihood of conversion. Detailed explanations of each organizing theme are provided below.

Time

Nearly all the interviewees highlighted the importance of the Time theme. Time encompasses multiple dimensions, each carrying a distinct meaning. Within this theme, nine codes were extracted. In the context of a touchpoint, it is important to consider the specific time of day at which the interaction occurs. Many users engage with a brand or convert at consistent times. Therefore, if a user typically converts in the evening, greater weight should be assigned to touchpoints that occur during that time for that specific user.

Similarly, the day of the week can influence the importance of touchpoints, as many users exhibit shopping behaviors that vary by weekday. Expanding the perspective, the month of the year can also serve as a significant feature. Based on user conversion patterns, an attribution model could assign more credit to specific months.

Many interviewees identified seasonality as a key factor, noting that its effect may differ across industries. While the specific year of a touchpoint may not directly impact the attribution model, interviewees considered it valuable for analytical purposes. The year can help monitor broader contextual factors such as the competitive landscape, economic conditions, technological advancements, annual campaigns, or changes in consumer trends and behaviors.

Consumer preferences may evolve over time, and tracking the year can help identify trends—for example, the increase in mobile usage or shifts in social media engagement. The emergence of new technologies introduces new types of touchpoints across previously unconsidered channels. One such example is the rise of voice search, which has recently created novel interaction points for users.

Holidays were also mentioned as important time-based features. Holiday campaigns can significantly influence user behavior and conversion likelihood.

In addition to features tied to individual touchpoints, temporal data can also serve comparative functions, such as measuring the duration between the current touchpoint and the previous one. This interval can reflect user engagement patterns. Some users revisit websites multiple times in a short period without converting, while others may convert soon after a previous interaction. This variability highlights the importance of timing and frequency in customer journey.

Another key time-based feature mentioned was the time elapsed since the first visit. Although some interviewees believed this factor is more relevant in B2B contexts, others viewed it as an indicator of customer lifetime value, journey length, personalization opportunities, or engagement levels. A shorter journey may suggest effective marketing, while a longer one may reflect user hesitation or the need for repeated engagement to build trust.

Additionally, several interviewees—particularly those focused on practical applications of attribution modeling—emphasized the usefulness of the "days from conversion" feature. They noted that historical data can help predict this duration. Understanding this metric allows for credit allocation that reflects the recency of touchpoints, aligning with principles used in the time-decay attribution model, which assigns greater value to interactions occurring closer to the conversion moment, based on their assumed stronger influence in the decision-making process.

- **Technology**

Themes within the "Tech" category pertain to the types of technology used by the user. This category could help with personally customizing users. While some interviewees felt that technology-related features might not significantly impact attributing to touchpoints, others suggested that the influence of these features could vary depending on the specific industry and business structure. However, all agreed that understanding the technology used by users could provide valuable insights into individual behaviors, preferences, or interests. Also, the interviewees highlighted that these features of touchpoints affect the presentation of touchpoint and how these touchpoints appear for a user, which can significantly impact the user's experience and perception of the touchpoint. This theme consists of 6 sub-themes: browser type, browser version, operating system, device type, internet protocol (IP) address location and language. These features are infrastructure-related and describe the technical context or platform of the touchpoint. Browser type refers to the software the user employs to access content. Different browsers render websites differently and vary in speed and compatibility. If a browser causes lag or breaks page features, the user might leave, resulting in poor engagement. Browser type can also reveal demographic information; for example, Safari users often use Apple devices (potentially higher income), while Firefox may attract privacy-focused tech enthusiasts. These characteristics extend to the browser version. Whether the version is the latest, recent, or outdated affects performance, compatibility, and technical context. Newer versions support modern web features such as fast checkouts or rich media, while outdated versions might fail, leading to abandoned transactions (e.g., a broken cart checkout), which could reduce conversions despite strong advertising. Furthermore, outdated versions might indicate less tech-savvy users or older devices.

Operating systems can also play an important role, depending on the target audience. iOS (iPhone operating system) often correlates with higher purchasing power; Android's diversity may reflect on-the-go shopping, and Windows might dominate desktop purchases. Thus, if a company targets a broad audience, Android and Windows users might represent better prospects. As one interviewee explained, "Mobile users often browse quickly or shop on-the-go (high intent, short sessions), desktops support detailed research or big purchases, tablets blend both." This comment underscores the significance of recognizing the device type being used.

Companies should tailor their ads according to the device to boost the user experience. Mobile devices might limit visibility (e.g., smaller ads), while desktops offer richer interactions. Therefore, ads containing extensive written content may not engage users effectively on mobile devices, which typically have smaller screens.

An Internet Protocol (IP) address is a numerical label assigned to a device connected to a network and reveals information about the user's location and Internet Service Provider (ISP). Geographic context can reveal purchasing power, shipping feasibility, or cultural preferences. For example, a touchpoint in a high-income region might convert more frequently. Additionally, for businesses operating in multiple regions, location might correspond to local holidays or sales events (e.g., Black Friday). This feature allows companies to emphasize key market locations and analyze location-based patterns (e.g., urban vs. rural conversion rates).

Among the interviewees, a few mentioned language as a touchpoint feature, noting that language preference might affect user intent. A touchpoint in a user's native language may engage better than one in a mismatched language. It is worth noting that these features do not operate independently; rather, their combination contributes to effective attribution of touchpoints.

- **Marketing**

This category focuses on marketing aspects of a touchpoint and reveals the roles of marketing strategies at each point of contact. It illustrates how each sub-feature provides insights into different aspects of marketing efforts. These marketing efforts interact with potential customers throughout their buying journey. These features are crucial because they bridge the company's marketing actions to user responses, helping attribution models determine which aspects of strategy drive value. This organizing theme consists of seven features: channel type, campaign medium, campaign purpose, position in journey, message type, keywords, and demographics.

Examples of channel types include organic search, paid search, social media, email, and display ads. Channel type represents the source of traffic and specifies where the user comes from, while each channel has its reach and impact. By extracting these features from touchpoints, valuable information can be gained. For example, paid-search channels target intent, social media channels build engagement, and organic search reflects SEO (search engine optimization) success. Marketing performance analysts expressed that high-intent channels such as paid search might drive quick conversions, while others nurture leads over time. Therefore, it is crucial to attribute the correct amount of credit to each of the touchpoints in each channel.

Additionally, campaign medium, which represents how the message is presented, is considered significant. Email, display ads, and banner ads are examples of media. Delivering an advertisement in a campaign matters since, for example, email is personal, display is visual, and text ads (or paid search ads) are search-driven. Each affects engagement differently.

Another feature related to marketing categorization is campaign purpose, which is also pivotal. Purpose reflects the intent of the advertising. Awareness, engagement, conversion, and retention are examples of campaign purposes. Each of these purposes shapes the journey's arc. An awareness touchpoint introduces and informs the user and might not convert directly, but sets the stage, while a touchpoint with a conversion purpose seals the conversion. Both matter differently. These purposes can also be aligned with the user's position in the journey. Position shows where the touchpoint fits; upper-funnel, mid-funnel, or lower-funnel stages have unique roles, and different touchpoints should be placed accordingly in each position of the journey.

In this study, message types have also been considered a feature of touchpoints. Whether the message is informational, promotional, or emotional drives different responses and triggers different actions educate, promotional messages incentivize, and emotional messages build bonds. They can impact conversions differently; a promotional discount might persuade quick buys, while an emotional storytelling message builds loyalty. This feature is closely intertwined with the purpose of the campaign, such that, for example, promotional touchpoints might earn higher attribution for direct sales purposes and emotional touchpoints for retention purposes.

Experts discussed keywords related to touchpoints. Keywords, whether informational, transactional, or navigational, reveal what the user seeks. If a user searches for the keyword "buy Nike Air Max shoe" (transactional), it signals readiness; "reviews on Nike Air Max shoes" (informational) signals exploration; and "Nike Homepage" (navigational) signals a direct intention to visit a specific website or brand's official online presence. Intent drives conversion probability: a touchpoint tied to transactional keywords might convert faster than informational ones.

The last feature in this category is demographic features. Demographics define who is reached; for example, ages 18–24 might prefer trendy ads, while those aged 45+ value reliability. Gender might sway product appeal. Also, based on the target audience and behavioral trends, attribution to touchpoints could differ; young females might engage more with emotional messages, while older males might respond more to promotional messages, tailoring impact.

- **Visits**

The "Visits" category consists of seven features: page view, engagement depth, landing page/exit page, session duration, bounce rate, visitor status, and frequency of visits. These features capture how a user interacts with an e-commerce platform during or after a touchpoint, reflecting levels of engagement, user intent, and behavioral patterns.

Page view depicts the activity level and counts how many pages a user views in a session. This feature is associated with sessions and concurrently pertains to a specific touchpoint. A touchpoint can lead to a high number of page views and initiate broader engagement. More views could indicate that a touchpoint sparked curiosity or encouraged deeper site navigation, although experts believe this is not always the case. This feature leaves an indirect footprint, meaning it is used as "pages triggered by this touchpoint."

The second feature in this category is engagement depth, which measures how deeply a user engages with the content. For instance, if a user scrolls through 80% of a webpage, watches 60 seconds of a video, or clicks three times, it suggests an interest beyond a casual glance. A user who watches only three seconds of a video shows lower engagement than one who watches 50 seconds, potentially reflecting curiosity about the product. Deeper engagement often indicates stronger consideration.

The landing page and exit page also provide informative insights. The landing page represents the entry point; for example, entering on a product page signals intent and might drive sales. Conversely, the exit page, such as a checkout page, reveals drop-off or completion—it may indicate a purchase, abandonment, or hesitation. When it is presumed that a user might leave at the checkout (or cart) page, another touchpoint with higher value could potentially lead to conversion.

Another feature related to the strength of user engagement is session duration. Many experts noted that the time users invest is a crucial indicator. Longer sessions—such as browsing products or reading detailed content—suggest greater interest or deliberation. Like page view, this feature is session-related, but a touchpoint that leads to a long session may have effectively captured the user's attention.

Closely related to this is the bounce rate. A high bounce rate means the user left quickly, possibly after viewing only one page. In contrast, a low bounce rate suggests "stickiness," indicating that a touchpoint successfully encouraged the user to explore further. However, it is important to note that a high bounce rate does not necessarily imply a lower value for the touchpoint, especially if the user is still in the early stages of the journey.

This leads to another important feature: visitor status. Visitor status identifies the type of audience based on the customer lifecycle. New visitors explore, returning visitors consider, and loyal customers commit—each stage reflects a different intent and value. A touchpoint attracting new visitors may build awareness, while one targeting loyalists may drive repeat purchases. It is crucial to determine whether to attribute higher value to touchpoints that convert loyalists or to those that turn new visitors into returning customers.

Finally, the frequency of visits reveals the consistency of user engagement by measuring how often a user returns. Frequent visits may be tied to a touchpoint that keeps users coming back and signals loyalty. While high frequency does not guarantee conversion, these features should be viewed holistically. They are complementary and should be considered together, rather than in isolation.

- **Events**

The fifth categorization belongs to events. Event features are related to a specific action taken by a user during or immediately after a touchpoint. Similar to other categories, events reflect behavioral outcomes and progression towards conversion. Events are crucial because they provide concrete and action-based evidence of a touchpoint's impact. These features move beyond exposure or engagement and depict tangible steps in the customer journey. This organizing theme consists of 6 basic themes: Micro conversions, views, selection of items, basket, card, and purchase.

Micro conversions are actions that are small but meaningful towards loyalty, such as signing up for a newsletter or creating an account. These actions are an initiation of interest or trust. This means a touchpoint has successfully pushed the user beyond just passive browsing. The second feature, views, depicts curiosity. Viewing an item, product list, or a video deepens engagement.

A touchpoint leading to prolonged viewing (e.g., time spent on multimedia) might reflect compelling content or product appeal. As another action item selection shows, the user is narrowing options and might shift from browsing to consideration. For example, clicking on a product is a deliberate action, closer to purchase than passive viewing. Some experts discussed that selecting an item might be a tipping point where a touchpoint's value shines.

Another feature of events that shows strong intent is basket-related actions; add to basket is a pre-purchase step; remove from basket might indicate hesitation, but still engagement. The role of a touchpoint can be modified by viewing the basket, which reflects the possible decision-making by the user. Adding to the basket signals a wish-list for future intent.

Another important feature of a touchpoint involves card-related actions. These actions indicate very close moments to conversion and show high commitment. Adding payment or shipping info marks the start of a checkout. A touchpoint that has reached this point is pivotal since it has overcome the barriers, such as trust.

The final feature is purchase or conversion. Purchase touchpoint is the endgame and has proven direct contribution to revenue.

Discussion

In the digital age and with the rise of new technologies and platforms, nearly all businesses maintain an online presence and are expected to provide a seamless customer experience. Businesses are performing in a multichannel environment and, for delivering a seamless and personalized experience, they are using omnichannel strategies. The moments of interaction between a customer and a company in an online environment happen through multiple digital touchpoints. The rise of online review platforms, social media, and mobile internet access has empowered customers with greater knowledge about products, services, competitors, and pricing; for that reason, e-commerce businesses are focusing on a smooth and effective customer journey design. Touchpoints must be designed with specific features to enhance customer engagement and journey effectiveness. Touchpoints are considered critical elements of the customer journey, and the quality of touchpoints impacts customer behavior and satisfaction (De Keyser et al., 2020; Kranzbühler et al., 2018). Kuehnl et al. (2019) believe touchpoints must be designed with specific features such as seamlessness and personalization to enhance customer engagement and journey effectiveness. Monitoring the customer journey and the touchpoints helps companies to understand what is happening and why it is happening. The nature of touchpoints refers to the channel in which the interaction occurs, categorized into physical and digital types (De Keyser et al., 2020). Therefore, the customer journey unfolds across both online and offline channels, with interactions taking place in each (Hu & Olivieri, 2020). This research has concentrated on online touchpoints. Online touchpoints are basically traceable and quantifiable, offering rich behavioral data. In contrast, physical touchpoints, such as in-store visitors, interactions with sales representatives, billboards, or word of mouth, are often more difficult to measure accurately and require indirect methods such as surveys, loyalty tracking, or observational data (Lemon & Verhoef, 2016). Due to this disparity in measurability, online touchpoints are often used more than physical ones in attribution modeling. Physical touchpoints occur in a specific time and place, making them subject to contextual factors such as store conditions, ambience, and human interaction (Lemon & Verhoef, 2016). While online touchpoints are more asynchronous and location-independent, enabling marketers to reach their customers across geographies and time zones with personalized messages. Physical touchpoints, particularly those involving human contact, embrace human warmth and can foster stronger emotional engagement and relationship-building (Shankar et al., 2011). Online touchpoints, although consistent and scalable, face challenges in developing the sensory and emotional depth of physical experiences (Pantano & Gandini, 2017). Online touchpoints are more likely to shape earlier stages of the customer journey, while physical touchpoints often play a critical role in final purchase decisions. Future attribution research should thus consider how to meaningfully integrate both online and offline types of touchpoints to avoid biased model outputs and better reflect the holistic customer journey.

Attribution models provide the opportunity to allocate a share of conversion to an online touchpoint along the customer journey, enabling marketers to assign marketing spend more accurately based on which channel has the most influence on the customer decision to convert. Many studies have focused on the algorithms of allocation, using techniques such as Markov chains, Shapley values, and regression, but it is also important to consider the features of touchpoints in these algorithms. Therefore, in this study, we have taken the features of touchpoints into consideration in a more granular manner, aiming to enhance the precision and effectiveness of attribution models by integrating detailed touchpoint characteristics. This approach allows marketers to deeply understand what the features of a touchpoint are that can be incorporated into a model that will result in a better comprehension of customer behaviors and effective targeting of the audience. By interviewing experts and academics in this field and applying thematic analysis, 35 basic themes were identified and grouped into 5 organizing themes and 3 global themes. These features do not act in isolation, and a combination of them reveals subtle influences on user journeys. The five categorizations of basic themes consist of Time, Tech, Marketing, Visits, and Events, each focusing on different aspects of touchpoint features:

Many scholars have highlighted Time features as crucial feature in touchpoints throughout the customer journey, categorizing them based on their impact into short-term and long-term (Cambra-Fierro et al., 2017, Van Nguyen et al., 2022). The importance of time is also emphasized in the time-decay attribution model, which according to proximity of touchpoints to conversion the attribution value increases which increases the attribution value of touchpoints based on their proximity to the conversion event. In this research, nine feature for a touchpoint regarding Time was identified. These features help marketers to understand and predict online users' behavior regarding time, providing valuable insights into when users are most likely to engage or convert.

Technology features are tailored to the technology used by online consumers and play a crucial role in understanding their technological behaviors and what are their preference for interaction. Six features were categorized in this group. Mobile users tend to make decisions on the go, often resulting in quicker conversions, while desktop users typically take more time to research and make decisions, potentially leading to longer conversion paths, while tablet users can depict both behaviors. Also, this categorization can show the personality and purchasing power of the online user. An up-to-date Safari browser might be a tech-savvy user with high purchasing power. If the target audience are located in a rural place in order to engage them through online touchpoints it is important to use their preferred language.

Marketing categorization indicates features related to marketing strategies. Seven features were categorized in this group. Anderl et al. (2016b) also highlighted the importance of the initiation of contact in their study, distinguishing between Firm-Initiated and Consumer-Initiated touchpoints. They also mentioned the browsing goal as a feature of a touchpoint whether its informational search or navigational search. These features are seen in this category as channel type and message type. It is crucial to identify how message reaches the user and what is the campaign purpose. Marketers take different decision based in the position of a user in online marketing funnel. Traditional attribution models such as Last-click overemphasized users sitting in lower-bottom of the tunnel. Therefore, incorporating these features leads to a more precise and effective marketing strategy.

Visits categorization pertains to the behavioral and engagement level of online user in each touchpoint. Seven features are listed in this category. These features were considered significant by experts because they reflect user's respond to marketing efforts. Knowing how many page the user has visited, how deeply was engaged, in which page has entered or from which page has dropped-off, how much time has spent, whether is a new visitor or returning visitor or loyalist visitor, and how many touchpoints have already occurred are questions that will be answered by the features of this category. A new visitor landing on a product page, scrolling 80%, staying 3 minutes, viewing 4 pages, then exiting at checkout page with low bounce, indicates strong intent and engagement. Such behavior is likely indicative of a conversion-driven journey.

Events categorization is related to actions taken by online user in each touchpoint. This category captures specific user activities, showcasing behavioral outcomes and steps towards conversion. Six features were identified for this category. Micro conversion actions are considered preliminary steps that lead up to a final conversion. Certain events such as subscribing to a newsletter, watching a product video, or interacting with product and purchase details, signals different level of user interest and purchase intent. A touchpoint tied to a purchase should be regarded as a critical or “winner” touchpoint, and the pattern of user behavior leading to this touchpoint should be considered a valuable blueprint for marketers.

These 35 features were structured in a way to cover temporal, technical, marketing, behavioral, and event-based aspects of touchpoints. It is important to note that these features do not exhibit a hierarchical relationship; each can play a significant role throughout the entire customer journey. Figure 2, a map of codes from MAXQDA, illustrates this fact.

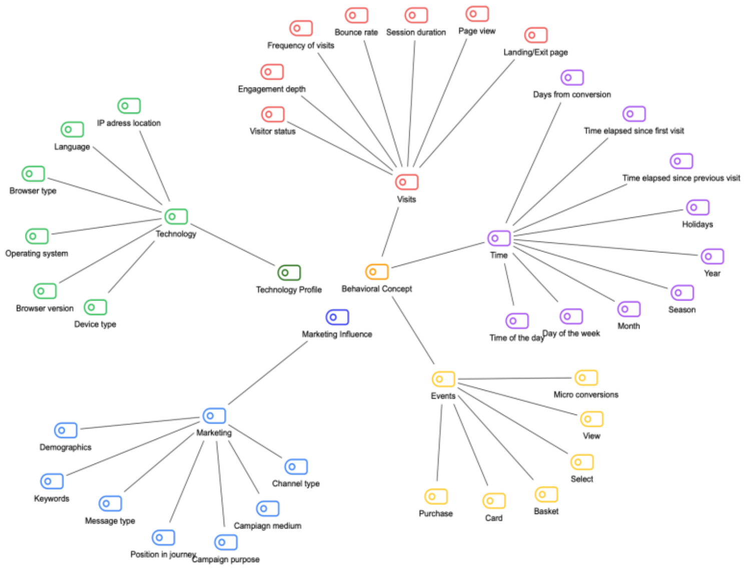

Figure 2. Codemap (extracted form MAXQDA software)

Conclusion

As demonstrated through this research, features of touchpoints were systematically categorized into five key areas: Time, Technology, Visits, Marketing, and Events. These features were identified by experts and academics in the field. These features aid marketers in understanding customer journey behavior and incorporating these insights into their attribution models. This holistic view of touchpoint features provides a valuable foundation for developing marketing strategies in an online omnichannel environment. This approach will enhance the ability to align marketing efforts with observed patterns of customer interaction. Like most studies, this research encountered some limitations. As a first limitation, access to experts in this field was not easy. A person that was considered as an expert should have met the required proficiency and be familiar with touchpoint concepts and multitouch attribution models. Qualitative data relied on human judgment. Therefore, based on interviewees' position and perspective, they might have held biased views. Some experts have overemphasized features they were more familiar with, such as emphasizing paid search over social media. Since the focus here was e-commerce, different businesses might have various priorities. However, this presumption has not been taken into account here. In this research, data saturation was achieved after nine interviews. Findings from a small sample might not reflect broader e-commerce trends. Furthermore, the economic conditions of the interviewees' country may influence their responses, which potentially may affect the results of the research. This research reflects the perceptions of the current e-commerce landscape, but this field is evolving every day, and new channels or AI interactions might emerge post-study. While this study concentrates on e-commerce in general, future studies could narrow down their focus to a specific e-commerce sector or specific geographical locations. Different geographical locations and even cultures might have different buying behaviors in this field. The results of this study could be applied in multitouch attribution models using different algorithms. Emerging technologies will play a significant role in future e-commerce; accordingly, investigating how emerging technologies, such as Artificial Intelligence, Virtual Reality, and Augmented Reality, influence touchpoints and customer engagement can provide valuable data for future marketing strategies.

Conflict of interest

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