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Bridging marketing theory and big data analytics: The taxonomy of marketing attribution

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ABSTRACT

The integration of technology in business strategy increases the complexity of marketing communications and urges the need for advanced marketing performance analytics. Rapid advancements in marketing attribution methods created gaps in the systematic description of the methods and explanation of their capabilities. This paper contrasts theoretically elaborated facilitators and the capabilities of data-driven analytics against the empirically identified classes of marketing attribution. It proposes a novel taxonomy, which serves as a tool for systematic naming and describing marketing attribution methods. The findings allow to reflect on the contemporary attribution methods' capabilities to account for the specifics of the customer journey, thereby, creating currently lacking theoretical backbone for advancing the accuracy of value attribution.

1. Introduction

Marketing analytics and specifically the accurate assessment of marketing performance, have long been priorities in business (Kotler & Keller, 2016; Rossiter, 2017). The proliferation of mobile and wearable devices has skyrocketed the number of potential touchpoints between consumers and service providers (Gartner Research, 2019; Gursoy, Chi, Lu, & Nunkoo, 2019). Technological innovations, including Big Data and advancements in data analytics, are revolutionising opportunities for businesses to establish effective communication with their target customers (Larson & Chang, 2016; Lemon & Verhoef, 2016; Senyo, Liu, & Effah, 2019). Customers can increasingly be provided with personalised experiences, and motivated to move along the purchase funnel to a conversion (Kannan, Reinartz, & Verhoef, 2016). Customer-centric marketing and integrated marketing communication strategies increase the length and the complexity of customer journeys, creating new challenges for marketing effectiveness analysis (Hosseini, Mohd-Roslin, & Mihanyar, 2015; Shirazi & Mohammadi, 2018).

Data-driven analytics, enabled by Big Data, information systems, technologies, methodologies and practices, allow the extraction of relevant data and its transformation into business insights (Anderl, Becker, von Wangenheim, & Schumann, 2016). The application of sophisticated methods of marketing attribution has been conceptually and empirically proven to be effective for optimising marketing return on investments (de Haan, Wiesel, & Pauwels, 2016; Kireyev, Pauwels, & Gupta, 2016). This has boosted demand for research and introduction of new, context-specific attribution methods (Ghose & Todri, 2015; Li & Kannan, 2014; Mukherjee & Jansen, 2017; Nottorf, 2014; Xu, Duan, & Whinston, 2014).

Rapid developments often lead to heterogenous and overlapping terms being introduced within disciplines (Bowen, 2009). A similar situation can be observed in the domain of marketing attribution. Aimed at identifying ways to improve the efficiency of marketing attribution., multiple studies apply the concepts of consumer decision-making and data-driven analytics to explain the logic of value attribution from marketing perspective (Anderl, Becker et al., 2016; Halvorsrud, Kvale, & Følstad, 2016; Hosseini, Merz, Röglinger, & Wenninger, 2018). A stream of research conceptualises the capabilities of the advances analytics and proposes specific methods for marketing communications' value allocation (Hülsdau & Teuteberg, 2018; Kannan et al., 2016; Wedel & Kannan, 2016). However, a framework that provides an exhaustive summary of all currently available attribution methods, explaining their capabilities and minimising the inconsistency of use of attribution terms application, is still missing.

The purpose of this conceptual paper is to develop a comprehensive tool for naming and describing marketing attribution methods. The paper first synthesises the concepts of consumer decision-making and the capability of data-driven analytics to provide it, in order to propose a

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framework for research. It then builds on the result of the analysis of the identified attribution methods' descriptions to extend the framework to mutually-exhaustive classes of marketing attribution methods. The major contribution of this paper is a new taxonomy of marketing attribution methods, which creates the background for systematic explanation of marketing attribution. The combination of deductive and inductive reasoning, applied in this paper, further enables reflection on the contemporary attribution methods' capabilities to account for the specifics of customer journey, thereby, creating currently lacking theoretical backbone for advancing the accuracy of value attribution (Saghiri, Bernon, Bourlakis, & Wilding, 2018).

This paper first conceptualises marketing attribution from the perspectives of the consumer decision-making process and applied data and analytics and proposes a framework for analysis. Then, it discusses the specifics of systematic literature search and qualitative content analysis, applied to classify attribution methods. The study then presents the developed taxonomy of marketing attribution. The paper concludes with a discussion on the advantages and limitations of this taxonomy. It further contrasts the identified classes of methods against the proposed conceptual framework, reflecting on their capability to accurately allocate value to marketing communications. To simplify comprehension, Table A1 in Appendix A summarises the definitions of the key concepts applied in this study.

2. Theory

Marketing attribution is a strategy of determining the value of marketing communications and allocating it to identified touchpoints along customer journeys (Econsultancy, 2015; Kannan et al., 2016; Moffett, Pilecki, & McAdams, 2014). Similarly to previously available methods, it utilises customer data and data analytics to generate marketing insights. The distinctive feature of marketing attribution is its capability to accommodate individual-level, high frequency Big Data and advanced analytical techniques. Together, these resources create a potential to acquire a realistic picture surrounding the role of customer touchpoints along marketing information and communication channels (further referred as "*channel*") on consumer behaviour (Moffett, Pilecki, McAdams et al., 2014).

2.1. Attribution capabilities

The accuracy of attribution depends on the methods' capability to allocate value to touchpoints in accordance with the real effect these touchpoints have on decision-making (Kannan et al., 2016; Larson & Chang, 2016). Each customer journey consists of a sequence of *touchpoints.* A touchpoint represents an interaction between a customer and a brand, which is experienced by the customer via a channel in the form of a marketing communication, such as a product or service advertisement. When developed for specific channels, the set of marketing touchpoints supports consumer decision-making and motivates them to convert (Kannan & Li, 2017). Nevertheless, each touchpoint can have a positive, negative or neutral effect on the customer's decision to continue interactions with a brand and to move along a purchase funnel (Anderl, Schumann, & Kunz, 2016). To enable accurate value allocation, marketing performance analytics require a comprehensive approach, which recognises the changes in consumer decision-making under the influence of a marketing communication.

Contemporary marketing recognises that each customer journey is a unique one. Every customer has specific motivations, determined by idiosyncratic preferences, which are shaped by socio-demographic characteristics, economic status, culture, individual beliefs and perceptions (Anderl, Becker et al., 2016). Moreover, consumer interactions with the service provider, their involvement in marketing communications, attitudes towards brands and purchase intentions can be dynamically affected by real-time changes of their contexts (Buhalis & Sinarta, 2019; Dwivedi et al., 2020). However, there is a common agreement that the characteristics of marketing communications and their timing in the customer journey would create a different effect on the customer experience.

According to the concept of integrated marketing communications, customer experience from a touchpoint depends on the specific parameters of this touchpoint. Multiple frameworks of marketing mix, including the 4 Ps (Hartley & Pickton, 1999), 4Cs (Smith, 2003), 7Cs (Thaichon & Quach, 2016) and 8 Ps (Melewar & Saunders, 2000), have been developed for different contexts, of consumption. However, there is a common agreement that the characteristics of a service and the way it address customer needs, the two-way communication between customers and service providers, the convenience of this communication for customers and the costs customers face shape their motivation to move along a purchase funnel (Thaichon & Quach, 2016).

To accurately allocate value to a touchpoint, it is important to recognise the difference in the effects that this touchpoint would have in the context of different products and services they support (Anderl, Becker et al., 2016; Sinha, Mehta, Bohra, & Krishnan, 2015). The contemporary market environment offers a range of channels, allowing both parties to optimise convenience of communications. Face-to-face communication remains influential for customer decision-making (Kannan & Li, 2017). Though, the scope of impersonal communications, performed via digital devices and smart infrastructure, such as Amazon Echo Speaker, prevails over in-person interactions for a range of services and makes some customer journeys fully digital. Due to the fact that consumer behaviour is motivated by existing needs (Kireyev et al., 2016), the corresponding parameters of a touchpoint are expected to have a different effect on customer conversion depending on the party that initiated the communication. Thus, customer-initiated communications with a service provider, including the access to a company website, social media or an online chat, have been proven to have sufficient influence on the final decision (Anderl, Schumann et al., 2016; Kizgin et al., 2020). However, research has demonstrated that the role of company-initiated communications, such as banners, newsletters or push notifications, is often underestimated (Anderl, Becker et al., 2016). Last but not least, each marketing communication is associated with varying costs for customers. Whilst not every touchpoint leads to a monetary expense, different contexts of consumption require customers to invest different amounts of time, cognitive and emotional efforts to access information and receive services (Zanker, Rook, & Jannach, 2019). As a result, each of the aforementioned parameters of a touchpoint may have a different effect on customer transition to conversion.

Following the ideas of the customer journey and purchase funnel, customers pass through distinct stages of awareness, interest, desire and action to satisfy their needs (Heuchert, Barann, Cordes, & Becker, 2018). Depending on the stage, the same touchpoint may have a different effect on the decision-making process, either triggering interest, desire and eventually conversion, or irritating and discouraging the customer from proceeding with the purchase. Importantly, the effect of a touchpoint on customer decision is dependent on the amount of marketing communications customers are exposed to (Anderl, Becker et al., 2016; Heath, Cluley, & O'Malley, 2017). Exposure to a range of touchpoints does not always have a cumulative effect (Berman, 2018). Nevertheless, the sequence of experienced touchpoints can have synergic or antagonistic effects on customer decision-making, thereby, increasing or ruining the effect of marketing communications (Nottorf, 2014; Sinha, Mehta et al., 2015). The complexity of interpreting consumer decision-making further increases due to the fact that the frequency of interactions can further change the effect of each touchpoint on the consumer buying decision (Sinha, Mehta et al., 2015; White, Hassan, Singla, & Horvitz, 2014). A preceding interaction can influence customer perceptions on the service, creating overlapping effects of different magnitudes within one channel (i.e. 'carryover effect') and between different marketing channels (i.e. 'spillover effect') (Anderl, Becker et al., 2016; Li & Kannan, 2014; Xu et al., 2014). It can also enforce or weaken the effect of the subsequent touchpoints. Instead of just analysing the effect of

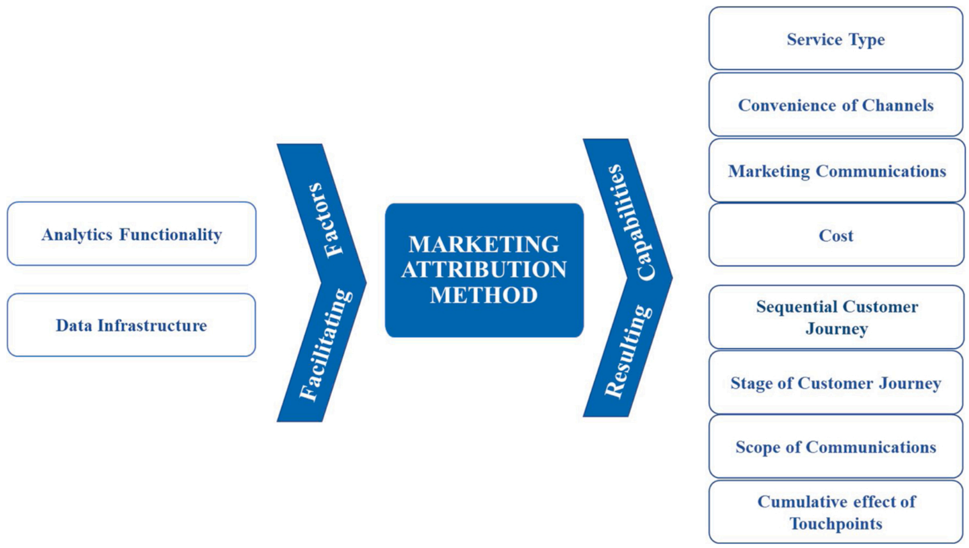

Fig. 1. Conceptual Framework of Marketing Attribution.

stand-alone touchpoints, the accurate determination of their value should be derived from the entire scope of touchpoints customers were exposed to. Finally, customer transition along a purchase funnel is rarely linear. Motivated by the aforementioned factors, they can access the same website or return to information search for several times. Moreover, their decision can be shaped by existing loyalties and the power of a brand (Kranzbühler, Kleijnen, & Verlegh, 2018). Accurate value allocation needs to be attributed to each touchpoint in the context of the specifics of a customer journey (Kannan & Li, 2017; Nottorf, 2014).

2.2. Attribution facilitators

The capabilities of marketing performance analytics for accurate determination of the effect, which a touchpoint has on customer conversion, are enabled by individual-level data and the approach for its analysis (Kannan et al., 2016; Larson & Chang, 2016). Comprehensive data modelling techniques have long been available to marketeers for observing the occurred interactions and predicting possible trends in consumer behaviour. However, available data and technologies were limited to estimations the effects of marketing communications on customer conversion by aggregating market data during the period under investigation and analysing it afterwards. The proliferation of personal devices, the Internet of Things and constant connectivity, generate massive volumes of Big Data. Such technologies enable observation of human behaviour, including their transitions along marketing channels and their exposure to specific touchpoints. A range of obstacles still prevent businesses from tracking the entire customer digital journey. They include legislation that enables customers to prohibit service providers from tracking their data or delete their data, such as search history and cookies, from devices, technical issues that prevent synchronisation between devices or do not allow service providers to observe if a user has been exposed to an advertisement, placed at the bottom of a webpage, as well as the inability of accurate offline observations of consumer behaviour (Wooff & Anderson, 2015). However, the scope and accuracy of data are constantly improving, enabling the application of advanced analytics and producing new insights on consumer online buying behaviour.

The capability to integrate specific metrics into an attribution method determines its ability to account for different types of touchpoints and accurately allocate value to each of them. Attribution methods widely apply countable indicators, such as number of website visits, number of exposures, impressions and clicks on banners and email newsletters and conversion rates (Anderl, Schumann et al., 2016; Li & Kannan, 2014; Sinha, Mehta et al., 2015). The possibility to collect such metrics from multiple channels, including company website, search engines, affiliated websites, social networks) and multiple devices (e.g. PCs, mobiles, tablets, kiosks) is increasing. It is still relatively difficult to track individual exposures to offline advertisements and promotions. However, contemporary technologies, including GPS and cell-phone signal tracking, allow the relation of offline touchpoints indirectly to the observed customer activities. The proliferation of sensors and smart infrastructure (Buhalis, 2020) additionally enables marketers to collect data about real-time customer context (Buhalis et al., 2019), including exact places and times of visits, undertaken activities and social environment (Hashem et al., 2016; Ismagilova, Hughes, Dwivedi, & Raman, 2019). Marketing performance assessments have long utilised single channel analytics, such as Website traffic, Facebook likes and engagement, as they enable almost real-time observations of consumer behaviour based on individual level data. A combination of user data from online and offline channels and all devices, available for marketing attribution, allows to interpret customer exposure to different touchpoints, creating potential for more accurate value allocation.

Marketing attribution applies a range of analytical methods that vary from simple descriptive methods to artificial intelligence-based solutions (Duan, Edwards, & Dwivedi, 2019). Many of them were conceptually proposed during the last decades, but largely remained unapplied in marketing (Larson & Chang, 2016). Large data warehouses and increased computational capabilities of devices, including cloud technology and artificial intelligence, have empowered marketers to benefit from advanced analytics, which accommodate the processing of more complex tasks (Dwivedi et al., 2019; Mahroof, 2019). These approaches enable partial or full automation of attribution processes, augmenting observation, interpretation, evaluation and allocation of value and making this process less time-consuming and less skill-intensive. Together, such techniques have potential to boost the accuracy of the analysis and the capabilities of decision-making (Gupta, Kar, Baabdullah, & Al-Khowaiter, 2018).

2.3. Conceptual framework of marketing attribution

Attribution as a concept has been recognised as a marketing effectiveness analytics tool that can outperform widely adopted tools such as marketing channel performance analytics, and marketing mix modelling, in optimising marketing budget allocation (Berman, 2018). Such

Table 1
The Keywords for Systematic Search of Secondary Data Sources.

Meaning	Key words used for search
Research phenomenon	Attribution
Marketing performance and purpose of attribution	Marketing, touchpoint, sales, conversion, source, return on investments, ROI, click, advertising, marketing campaign, customer journey, value, credit
Marketing analytics and attribution facilitators	Modelling, Model, Multi-channel, Omnichannel, Cross-channel, Last click, First click, Last touch, Rule-based

potential has triggered a stream of empirical research (Table B1 in Appendix B). The combination of multiple types of Big Data, analytical techniques as facilitators of attribution and capabilities of the methods to account for specifics of consumer behaviour along a purchase funnel, enable the existence of multiple methods of marketing attribution with different functionalities and varying capabilities to allocate value to multiple touchpoints (Kannan et al., 2016). The attempts to present such functionality further lead to co-existence of multiple overlapping terms, that name and describe the attribution methods. For examples, the terms "multi-channel", "omni-channel" and "cross-channel" attribution highlight similar capabilities of the methods to account for multiple touchpoints of a customer journey. However, a unified approach that would systematically define all existing methods, reflecting their functionality and providing a clear distinction between them, is missing.

Understanding the exact effect that marketing messages have on customer conversion requires a holistic and customer-centric approach (Kannan & Li, 2017; Lemon & Verhoef, 2016). The advantage of marketing attribution is its capability to account for each individual customer journey and then aggregate the insights into trends to enable marketing planning. Marketing attribution methods would benefit from available data, which characterises marketing touchpoints, and analytical techniques, which can derive the insights from the data, to realistically present each touchpoint. Such a presentation would account for the parameters of marketing mix and specifics of decision-making along a customer journey. Fig. 1 summarises the facilitators and expected capabilities of marketing attribution and proposes a holistic framework for defining marketing attribution as a marketing performance analytics tool.

3. Materials and methods

The purpose of this conceptual paper is to develop a comprehensive tool for naming and describing marketing attribution methods. Taxonomies are the schemes, which serve to organise a collection of subjects into classes. Such classes are identified based on distinctive characteristics of the phenomenon, and, therefore, would be mutually exclusive. Together, they would provide an exhaustive overview of a research phenomenon, enabling the systematic classification of the observed subjects (Nickerson, Varshney, & Muntermann, 2013). This paper follows the principles of taxonomy development and further discusses the details of data collection and data analysis, applied to ensure that all distinctive characteristics of marketing attribution methods are recognised.

Systematic literature search is a multistage method of data collection, aimed to select relevant secondary sources of information for the subsequent analysis (Denyer & Tranfield, 2009). While the stages can be described differently, systematic literature search methodology follows the common principle of identification of relevant keywords, that would answer a research question, locating sources based on those keywords, analysing the quality of the located sources and filtering out those sources that do not meet inclusion criteria (Khan, Daya, & Jadad, 1996; Rouhani, Mahrin, Nikpay, Ahmad, & Nikfard, 2015; Wilding, Wagner, Colicchia, & Strozzi, 2012). The purpose of this study was to minimise the inconsistency and overlapping nature of applied terminology in the marketing attribution domain. The systematic literature review search and analysis methods were selected based on their capability to incorporate as many relevant sources as possible, and to ensure reliable inferences.

3.1. Identifying keywords

The definition of marketing attribution and related concepts (Table A1 in Appendix A) and the proposed conceptual framework (Fig. 1) allowed to formulate a set of keywords for systematic literature search. Such keywords named the phenomenon itself, described the purpose of its applications and the commonly applied characteristics of the methods (Table 1). Each search query included the combination of keywords with search operators in a way that they always included the term "attribution" with either one of its applications contexts characteristics or one of the methods' characteristics (e.g. "Research phenomenon" AND "Marketing performance and purpose of attribution" OR "Marketing analytics and attribution facilitators").

3.2. Locating sources

Applying multiple sources and their consequent triangulation enables generation of a comprehensive explanation of a research phenomenon (Creswell & Poth, 2017) and cross-validation of findings (Krippendorff, 2013). The sampling strategy included both academic peer-reviewed publications and available industry sources, such as white papers, published by independent research and consultancy agencies, and reports by the leading attribution vendors, as these are often the most updated sources of information. The publications in peer-reviewed journals and conference papers in the domains of business, management, marketing, computer science, economics, as well as mathematics were retrieved from Scopus, Science Direct and Google Scholar databases. The Google Search engine was additionally used to identify reports by independent research and consulting agencies and the leading marketing attribution vendors. The study aggregated the list of all possible sources that met keyword search criteria, without any restrictions of time of publication and journal ranking.

Considering the developing nature of marketing attribution and its terminology, the information search by keywords was supplemented by the snow-ball sampling technique. The study explored academic sources, cited by the selected sources because of their capability to provide an explanation about the nature and types of marketing attribution. Both sampling strategies located 164 academic sources and 31 industry sources in total.

3.3. Selecting sources

The screening process applied several screening criteria and therefore, was done in several stages. First, it explored paper titles and dates of publication. Repeated studies and those, published before the massive proliferation of personal computing devices and Big Data, which enable attribution (i.e. before 2005), were excluded. This allowed the retention of 116 academic and 29 industry sources.

Secondly, the screening process analysed the abstracts and keywords of the remaining sources for the content, associated with the search criteria. The studies with no relationship to marketing attribution as a research phenomenon were excluded, even if they were related to the characteristics of marketing analytics in general or contained the relevant keyword. The outcome of systematic literature reviews largely depends on the quality of selected sources (Khan et al., 1996). Therefore, the additional two criteria: relevant methodology and the publishers being a recognised research & consultancy agency, were applied to ensure validity and reliability of selected industry content. The sources of a promotional nature were also eliminated.

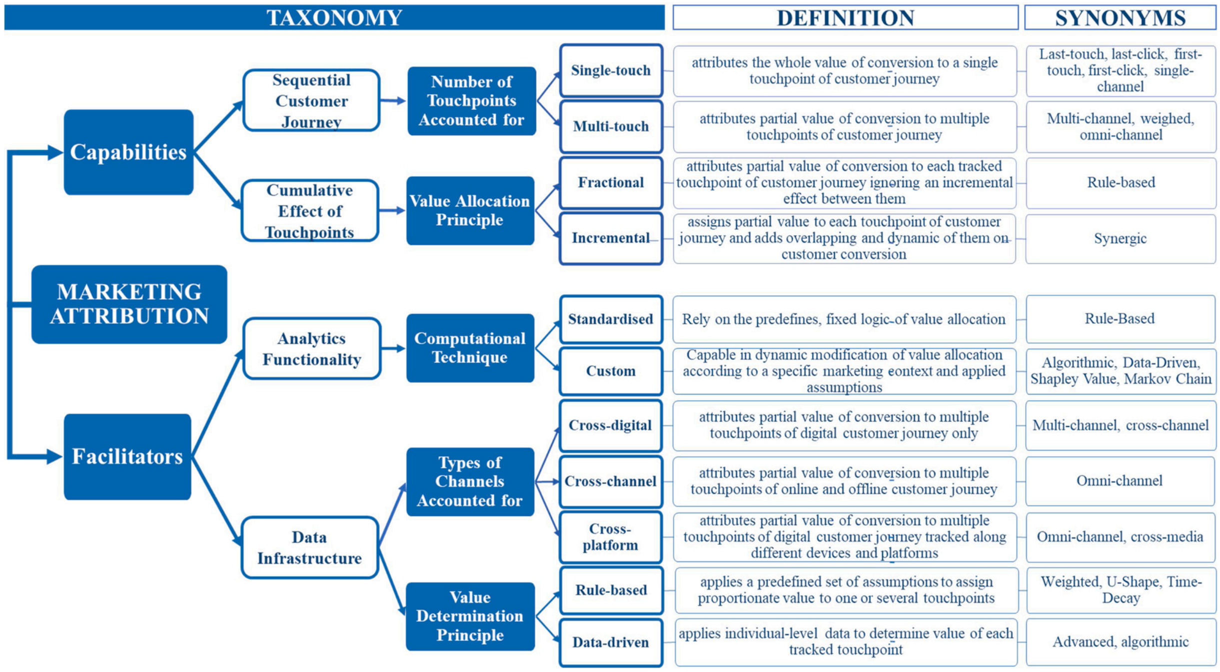

Fig. 2. Marketing Attribution Taxonomy.

As a result, 62 sources, including 26 studies from peer-reviewed journals, 16 conference papers, 7 research papers and reports by independent research agencies, 6 reports by attribution vendors in collaboration with independent research agencies and 7 white papers by leading algorithmic attribution vendors, were incorporated in the analysis (Table B1 in Appendix B).

3.4. *Analysing content*

Following the principles of taxonomy development (Nickerson et al., 2013), the study applied a combination of deductive and inductive approaches. It first deductively identified major dimensions of the phenomenon based on the concepts of big data analytics and consumer behaviour. This part resulted in the conceptual framework to guide the study.

The study then applied inductive reasoning by analysing the context of the selected sources. Considering the presence of inconsistent application of attribution-related terms, classifying the described attribution methods either by titles or by their properties might have created gaps in defining mutually-exclusive taxes. The study triangulated the results of 2 types of descriptive coding to categorise the existing attribution methods based on their properties (Krippendorff, 2013). First, it explored the content for categorical differences to identify distinct titles, applied to define a method, and all descriptions, associated with this term. The second round of coding explored the content for thematic differences to identify distinct descriptions of the methods and all terms, associated with the description. The elaborated themes, arising from the triangulation of findings, were matched with the hypothesised categories of marketing attribution. It also ensured that all attribution dimensions were included and reduced the probability of arbitrary or non-existing characteristics inclusion as a class (Nickerson et al., 2013). To finalise a taxonomy of currently existing methods, the conceptualised dimensions without empirically identified classes were eliminated.

4. Results: the taxonomy of marketing attribution

The themes that were developed as a result of the qualitative content analysis prompted the allocation of existing marketing attribution methods into classes within the proposed categories of the conceptual framework. Fig. 2 introduces a second-order hierarchy of currently described marketing attribution methods. The first order represents the facilitating parameters and resulting capabilities, which can be used to describe any method. The second order represents mutually-exclusive classes, which the properties allow to distinguish between the different methods. Each class can incorporate a range of methods, which differ from each other by other facilitating parameters and capabilities. Together, they propose a holistic way to describe a marketing attribution method.

4.1. *Attribution capabilities*

The study has identified two characteristics of consumer behaviour, which are systematically addressed in the attribution methods. While several studies demonstrate that it is possible to model other characteristics, the qualitative analyses haven't identified their systematic application and the presence of specific terms, used to define those methods. This section further defines each of the proposed classes and then summarises the basic capabilities of the corresponding methods.

4.2. *Sequential customer journey: the number of touchpoints*

Historically, single-touch and multi-touch attribution were identified as two major groups of methods. *Single-touch attribution*, sometimes referred as a 'single-channel', tracks a single type of metric and assigns the total value of conversion to a single marketing touchpoint along the customer journey. The earliest methods of this type are the 'first-click' and 'last click' models, which assume that a desired user activity is determined by the initial and final touchpoint the consumer experiences, accordingly. Therefore, single-touch attribution is sometimes referred to by the name of the abovementioned assumption.

Multi-touch attribution distributes the total value of the occurred conversion across several touchpoints within the observed customer journey (Shao & Li, 2011; Wooff & Anderson, 2015). Earlier studies discuss it in the context of a solely digital environment, which is related to the earlier availability of the digital data in comparison to offline touchpoints. Currently, multi-touch attribution summarises a variety of methods from the point of view of applied metrics, accounted channels and applied formulas of weight allocation to the touchpoints (Shao & Li, 2011; Wooff & Anderson, 2015). This capability leads to occasional confusion and the interchangeable use of the notion 'multi-touch' and the names of the specific cases of attribution, such as 'weighted attribution' (Wooff & Anderson, 2015).

There is a common agreement that the advantage of single-touch attribution is its simplicity and availability for businesses (Lee, 2010; Xu et al., 2014). It is proven to be effective for short customer journeys. However, it provides biased results when assessing long customer journeys as it fails to provide a realistic view of the purchase funnel. Thus, single-touch attribution methods ignore details such as timing, the sequence of all impressions from touchpoints occurring between the first and the last (Li & Kannan, 2014; Xu et al., 2014) and causal relationships between these touchpoints (Sinha, Saini, & Anadhavelu, 2015). Therefore, multi-touch attribution, which tends to create a more realistic view of customer journey, is commonly believed to be a more accurate method of value allocation comparably to single-touch methods.

4.2.1. Cumulative effect of marketing communications: value allocation principle

The potential synergic effect of earlier experienced marketing communications on the next touchpoint and overall decision, results in two types of value allocation principles in attribution methods: fractional and incremental attribution. *Fractional attribution* assigns proportionate value to each touchpoint independently from other communications, experienced along a customer journey (Anderl, Becker et al., 2016; Geyik, Saxena, & Dasdan, 2015). It was introduced as one of the primary types of multi-touch methods. Taking into consideration that the first methods were based on marketers' heuristics, rather than on empirically derived weights, the term 'fractional attribution' is sometimes used interchangeably with 'rule-based' methods, which name the principle of value determination (Barger & Labrecque, 2013).

Incremental or *synergic* attribution assigns proportionate value to each touchpoint within the customer journey, while also accounting for a cumulative effect between these touchpoints (Ghose & Todri, 2015; Hou, Zhang, & Gu, 2016; Nottorf, 2014; Yadagiri, Saini, & Sinha, 2015). Importantly, it is often presumed that a touchpoint would have a positive effect on customer movement from the preceding stage of the purchase funnel to the next one, so that an online purchase, subscription to a newsletter or downloaded information would result in the customer conversion. However, the applied interpretations of customer journey and its stages, and carry-over and spill-over effects between the touchpoints, vary along the studies (Abhishek, Fader, & Hosanagar, 2012; Heuchert et al., 2018; Li & Kannan, 2014; Wiesel, Pauwels, & Arts, 2011). This has prevented the study from introducing the class, which would group the methods, systematically accounting for the influence that same marketing communication may have at different stages of customer journey.

The advantage of fractional attribution is a relatively easy marketing ROI calculation (Raab, 2011), which explains its wide acceptance (Wooff & Anderson, 2015). However, it is commonly acknowledged that in comparison to incremental attribution methods, fractional attribution does not realistically represent consumer behaviour due to the need for a more complex modelling. Thus, at least one of the described incremental attribution methods accounts for the effect of a brand name and customer awareness of it on their conversion (Abhishek et al., 2012; Lemon & Verhoef, 2016). However, none of the reviewed methods tracks post buying behaviour, such as an indicator of loyalty, customer reviews, or consequent applications, to model it in the case of repeat purchases.

4.2.2. Dimensions, excluded from the taxonomy

The research in the domain of marketing attribution recognises the need to account for the factors, that would shape consumer behaviour along sequences of touchpoints (Bucklin & Sismeiro, 2009). The advancements in computational technologies and the increasing scope of individual-level data, accumulated about the customer, have the capacity to inform attribution methods. This becomes possible due to their capability to account for specifics of services, individual customers' interactions, and also the context of these interactions.

Thus, some attribution models enable marketers to account for differences in customer conversion depending on age, gender, family status, education and household composition (Abhishek et al., 2012; Ailawadi & Farris, 2017; Anderl, Becker et al., 2016; Ghose & Todri, 2015; Nielsen Visual, 2018; Nottorf, 2014; Sinha, Saini et al., 2015). Some methods differentiate the value, acquired from marketing metrics analysis, by distinguishing between the effect of company and customer-initiated communications on a possible conversion (Li & Kannan, 2014). In the case of the data-driven attribution, value allocation principles can be adjusted individually for each service. However, no unified framework or principle has been identified.

Moreover, there are inconsistencies that might prevent the development of a unified principle for accurate value allocation. For example, several studies equate the concepts of "marketing channel" and "marketing communication". A "Facebook channel" might refer to the performance of a banner as a type of communication without recognising the Facebook page itself as another touchpoint. Such an approach might be explained by the available data and metrics, defined by a marketing campaign. However, the explored studies do not provide evidence of the existence of a systematic approach that would account for realistic consumer behaviour.

4.3. Attribution facilitators

The content analysis revealed that the research largely focuses on data analytics and exploring its capabilities for marketing attribution. The studies explore the opportunities to benefit from an increased range of metrics along diverse range of channels and apply various computational techniques in order to increase the realistic representation of consumer behaviour by attribution methods. Importantly, the analysis reconfirmed that most of the studies explore both the capabilities of the data and advanced analytics, thereby, creating an overlap in the meanings, used to describe the proposed methods. This section reports the identified classes and proposes the new terms to avoid any existing confusion in definitions.

4.3.1. Data infrastructure: types of accounted channels

By the types of accounted marketing channels, marketing attribution methods can be classified as cross-digital, cross-platform and cross-channel. While each class has its specific characteristics, the current properties, associated with them, create a partial overlap in the classes. Thus, *cross-digital attribution* derives data for value attribution from touchpoints along several digital channels with no attempt to acquire data from offline channels (Mukherjee & Jansen, 2017; Tucker, 2013; Yadagiri et al., 2015).

Cross-platform attribution, also referred to as *cross-device* or *cross-web* attribution, incorporates an individual's data from multiple devices by synchronising accounts and matching metrics from different platforms e.g. Google Chrome for PCs and Android or iOS for mobile devices (Branch, 2018; Ghose & Todri, 2015; Kannan & Li, 2017; Nielsen Visual, 2018). The reliance on the Internet to synchronise digital data along devices creates an overlap between cross-platform and cross-digital attribution. However, cross-platform attribution is not limited to digital metrics only, and can potentially benefit from offline customer data, such as location.

Cross-channel, '*omni-channel*' or '*cross- media' attribution*, applies data both from online and offline channels. Depending on available offline metrics, some attribution models incorporate offline touchpoints from tracked online sequences. Some methods do not track the data, that describes consumer offline interactions, instead they adjust the value of online touchpoints, according to the influence that hypothesised offline communications can have on the online customer journey and the resulted conversion (Abhishek et al., 2012; Anderl, Becker et al., 2016). So, data infrastructure of a cross-channel attribution may align with a cross-platform one. However, the purpose of incorporating all touchpoints regardless of their online or offline context makes it distinct from the latter one.

Most currently applied attribution methods belong to the cross-digital group (Anderl, Schumann et al., 2016). This is determined by the availability of relevant individual-level data and the complexity of the required analysis. Value attribution to offline behaviour is still evolving, which makes cross-digital attribution suitable for brands that are predominantly present online (de Haan et al., 2016). Cloud computing and the growing opportunities to synchronise accounts across devices improve the capabilities of cross-platform and cross-channel attribution (Xu et al., 2014). Thus, multiple methods propose the ways to differentiate between owned, earned and bought channels, and therefore, the differing effect a touchpoint may have depending on the customer role in it (Ailawadi & Farris, 2017; Anderl, Becker et al., 2016; Ghose & Todri, 2015; Kannan & Li, 2017; Kireyev et al., 2016). Therefore, a range of sources apply the term "omni-channel" or "advanced" attribution in relation to cross-channel and cross-digital methods. This emphasises their potential to provide more accurate value allocation in comparison to cross-digital methods.

4.3.2. Data infrastructure: value determination technique

The earliest adopted attribution methods, including the above-mentioned single-touch approaches, belong to the group of standardised frameworks for value allocation. *Rule-based attribution* incorporates applies predefined sets of theoretically established assumptions (rules) to assign value to one or several of the marketing communications customers have been exposed to. For example, the abovementioned 'weighted attribution' allocates a proportionate value to each of the identified touchpoints. A 'U-shape' method assigns a greater value to the first and last experienced touchpoints and a lower value to those in-between. In a 'time-decay' method the closer a touchpoint is to conversion the greater weight it receives (Adometry by Google, 2014; Wooff & Anderson, 2015).

Data-driven attribution applies individual-level data to identify both sequences of touchpoints and to empirically determine the relative role of each touchpoint in customer conversion (Wooff & Anderson, 2015). It can incorporate both channel-specific metrics, for example, type and size of an advertisement, time, length and frequency of website visits (Li & Kannan, 2014; Sinha, Saini et al., 2015) and customer context parameters, such as IP address, browsing history, keywords used for search, device type, browser type, length of sessions, location, gender and age (Ghose & Todri, 2015; Nielsen Visual, 2018).

The advantage of rule-based attribution is its simplicity and ease of application for businesses (Lee, 2010; Xu et al., 2014). It does not require advanced analytics and related financial and time inputs to acquire results. Its major drawback is the heuristic nature of value determination and inability to account for customer journey dynamics (Li & Kannan, 2014; Sinha, Mehta et al., 2015; Xu et al., 2014). Therefore, rule-based attribution methods cannot provide precise and reliable results (Lee, 2010). In comparison to heuristically-determined weights of rule-based methods, empirically- elaborated data-driven value attribution is proven to be more accurate, especially in cases of long customer journeys (Nichols, 2013). Therefore, data-driven attribution is also sometimes referred to as an 'advanced' approach (Rakuten Marketing, 2015; Visual, 2018).

4.3.3. Functionality: computational techniques

Earlier attribution methods such as rule-based attribution, apply standardised frameworks for value allocation. Such frameworks normally apply simple linear equations. For example, U-shaped attribution, applied for a customer journey of 3 touchpoints, assigns 40 % of value to the first and last touchpoint, whilst valuing the middle touchpoint as only 20 % of the conversion. The reliance of rule-based value allocation on the standardised set of assumptions motivates multiple studies to equate this method with 'rule-based attribution' (Lamont, 2014; Skillen et al., 2014; Zhang, Wei, & Ren, 2014). However, touchpoint weight coefficients can be also acquired from predictive modelling of each specific case. Therefore, the equalisation between 'rule-based' methods and 'not modified methods' is not fully acceptable. To reflect the standardised and predefined nature of computational principle, this study proposes the new term '*standardised attribution*'.

An alternative computation principle allows for the identification of a trend, relevant for a specific dataset, and applying it in the weight allocation formula (Sinha, Saini et al., 2015; Wooff & Anderson, 2015). The application of Big Data enables the dynamic elaboration and adjustments of the standardised principles, leading to sophisticated mathematic models to be introduced (Larson & Chang, 2016). It can utilise linear or logistic regressions (Shao & Li, 2011; Wiesel et al., 2011) and incorporate analytical tools such as machine learning (Abhishek et al., 2012; Li & Kannan, 2014) and cooperative game theory to generate results (Abakus, 2013; Berman, 2018). The dependence of such methods on both data and sophisticated computational methods often leads to the interchangeable application of the terms 'algorithmic' and, sometimes, 'data-driven' attribution. However, an algorithm is a 'procedure for solving a mathematical problem (as of finding the greatest common divisor) in a finite number of steps that frequently involves repetition of an operation' (Merriam-Webster, 2019). Both in mathematics and computer science the term 'algorithm' refers to a sequential method of problem solving (Techopedia, 2019; Wolfram MathWorld, 2019), which is applicable to all types of attribution methods. The main advantage of these approaches is their capability to provide an individually designed model. Therefore, the study borrows the term, applied by Google Inc., to describe the analytical capacity of the method to be modified, i.e. '*custom attribution*'.

Custom attribution is often described as being able to provide a more realistic view on the customer journey. Such methods have a computational capacity to account for all events of the customer journey (Lee, 2010), customer heterogeneity and the overlapping effect of multiple marketing touchpoints (Li & Kannan, 2014). Despite requiring relatively high expenses to implement it, custom attribution sometimes performs similarly to simplistic rule-based approaches. Relatively low performance is sometimes explained by its limitations in terms of input metrics, available scope of data, variables incorporated, as well as the incapability of the models to adapt to the specifics of the industry (Anderl, Schumann et al., 2016; Kannan et al., 2016; Kireyev et al., 2016; Nottorf, 2014). The reliance on the abovenamed factors makes custom attribution irrelevant for many organisations.

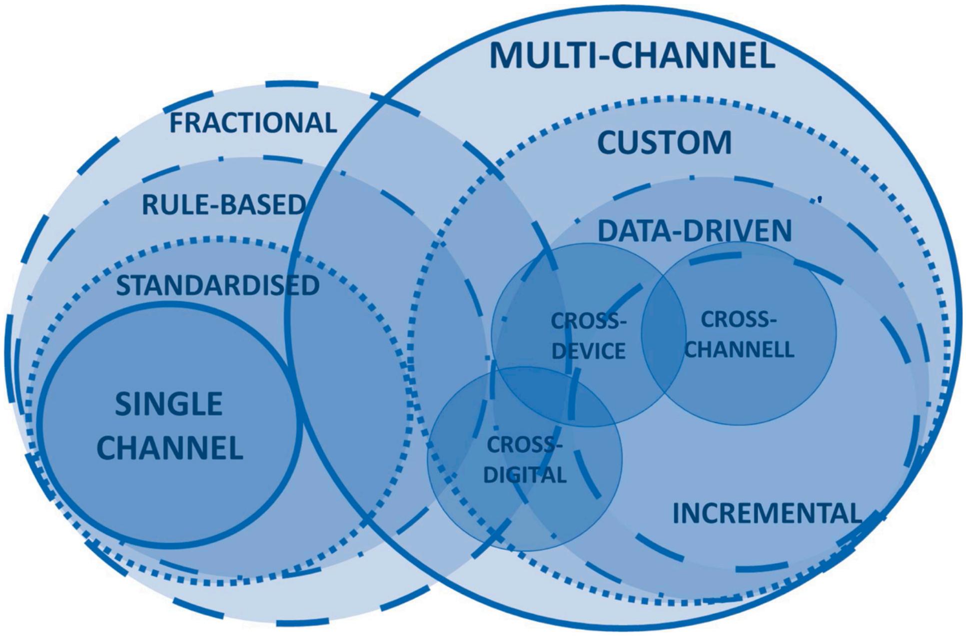

Fig. 3. Five-Dimensional Map of Marketing Attribution.

5. Discussion and conclusion

The growing number of available channels and types of marketing communications together with the changing customer behaviour makes attribution an important tool for optimisation marketing strategy and investments (Kannan & Li, 2017; Lemon & Verhoef, 2016). The original contribution of this paper in conceptualising marketing attribution as a marketing tool is twofold. The initial taxonomy provides a background to systematic classification of currently existing attribution methods. Supplemented by the proposed conceptual framework and map, it has created a novel theoretical background for advancing attribution methods.

5.1. A tool to describe an attribution method

Marketing attribution is a relatively new phenomenon, which has received widespread attention both by industry and the academia. This study has reconfirmed that the heterogeneity and overlapping character of applied terminology of developing fields (Bowen, 2009), is also evident in the attribution domain. It also demonstrated that some of the applied terms, such as "advanced" attribution, are implemented without an attempt to illustrate the specific method's parameters, but simply to highlight an improved capability of the method to allocate value in comparison to previously existing methods. The study addresses these issues by developing a way to systematically define the existing attribution methods and minimise any inconsistencies.

The main theoretical contribution of this study is the introduction of a systematic, theory-driven approach to describe and explain the existing methods of marking attribution. The proposed taxonomy of marketing attribution classified and defined attribution methods, presented in the marketing and data analytics domains, and organised them into a 5- dimensional second-order hierarchy. It further proposed new terms for two classes, that had been largely described but whose descriptions have been inaccurately embedded with other properties. The taxonomy provides a comprehensive overview of the marketing attribution typology.

Importantly, the first-order of the proposed taxonomy represents the diverse dimensions, relevant to be described for each method. The interdependence between attribution facilitators and resulting method's capabilities allowed to allocate the identified attribution classes in respect to one another. Fig. 3 illustrates all five dimensions and shows how each attribution type is related to other dimensions. If one of the parameters has been identified, the proposed map demonstrates what other facilitation factors and possible capabilities can be attributable to the method. For example, a cross-device attribution will likely be a multi-channel, custom-made and data-driven method, but can apply either a fractional or incremental value allocation. As a result, the findings create a background for a systematic explanation of any method and unification of the currently heterogeneous terminology.

5.2. The framework for attribution assessment

Attribution methods are evolving towards more sophisticated and inclusive approaches to incorporate more contextual factors, including specific features of a service, applied channels and marketing communications, as well as specifics of customer interactions with them. Increasingly, they tend to produce a more realistic view of customer journey and the effect marketing communications have on decision-making. The potential of cross-channel, data-driven, custom methods to improve marketing performance analysis has earned them the name 'advanced' (Bates, 2014; Wooff & Anderson, 2015). However, they still cannot ensure correct inferences about the consumer decision-making process (Abakus, 2013; Anderl, Becker et al., 2016; Carey, 2017). The full analytical capacity of value attribution has not yet been met (Ailawadi & Farris, 2017; Berman, 2018; Kannan & Li, 2017).

The proposed taxonomy demonstrates that there is no systematic incorporation of the methods that account for the specifics of customer decision-making. When compared to the conceptual framework of marketing attribution (Fig. 1), it can be seen that attribution methods address the need to account for the sequence of touchpoints and the potential cumulative effects between them. There are multiple studies, which aim to address specific aspects of the purchase funnel. However, a systematic approach to account for the parameters of marketing mix, is still missing. This indirectly suggests a need to improve attribution methods. This paper argues that the proposed framework can serve as a tool for assessing the potential of an attribution method to accurately allocate value of the customer conversion.

Customer journey becomes predictable as soon as technology can

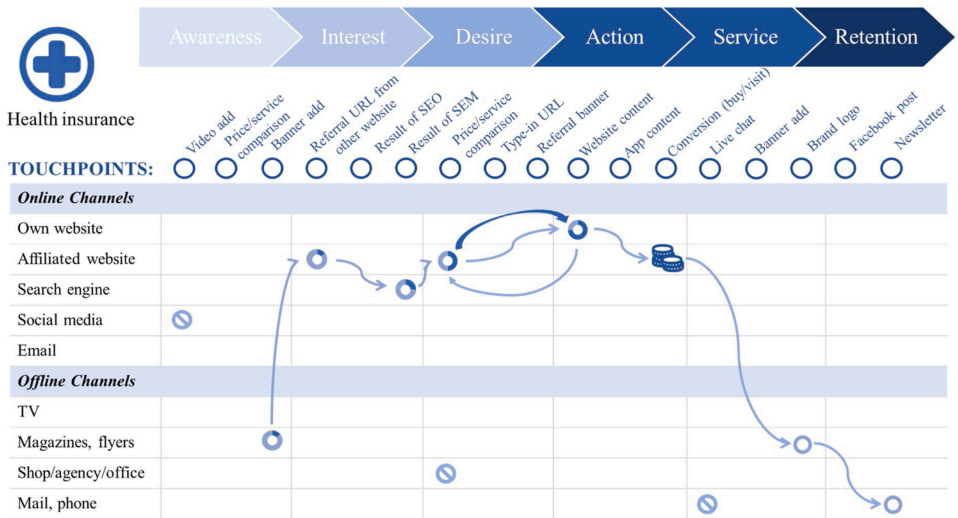

Fig. 4. Hypothesised Customer Journey for Health Care Insurance Service.

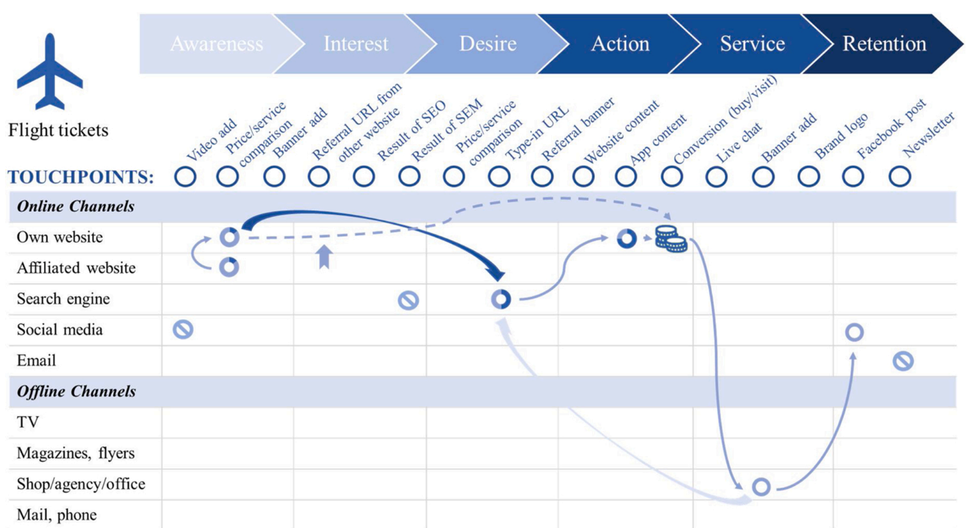

Fig. 5. Hypothesised Customer Journey for the Low-Cost Airline Tickets.

identify the parameters of a customer's internal and external context. The factors of internal context (socio-demographics, culture, individual knowledge, self-image, personality traits or disabilities) generate relatively stable preferences and often determine repeat purchasing behaviour. The external context factors, such as immediate location, time, weather, social environment, available information and technical capabilities and limitations of personal devices, affect customer needs in real time, potentially triggering impulsive buying behaviour (Buhalis & Sinarta, 2019). The proliferation of smart devices improved customer decision-making process on external factors, as these technologies eliminate restrictions of time and space in the process of communication between a customer and a service provider (Buhalis & Foerste, 2015). As a result, marketing communications, experienced before the interference of the contextual factors, may have no effect on customer conversion, making value attribution to multiple touchpoints irrelevant (Chan, Cheung, & Lee, 2017). Incorporating factors that describe customer context by attribution methods can provide the insights of marketing mix and purchase funnel for customer journey. To illustrate possible limitations, caused by the absence of the specifics of consumer decision-making on accurate value attribution, the study hypothesises three cases of distinctive consumer buying behaviour.

5.2.1. Health care insurance service

Health care insurance is a service that covers costs of medical expenses in the case of illness. Monetary costs always play an important role in consumer decision-making. However, in the case of health insurance, people tend to buy the most comprehensive plans to minimise their financial pressure and emotional uncertainty. (Berry, Davis, & Wilmet, 2015).

Health insurance is an intangible or credence service. Due to the lack of competence and experience, most customers cannot objectively evaluate the service (Gera, 2011). Marketing communications that provide customers with relevant information, respond to emotional state and evoke a perception of control over the service, are expected to have a positive effect on customer conversion. The customer journey in the case of health care insurance often represents a long, multistage and, sometimes, repetitive process (Fig. 4). It may include search and comparison between offers via providers' websites and face-to-face

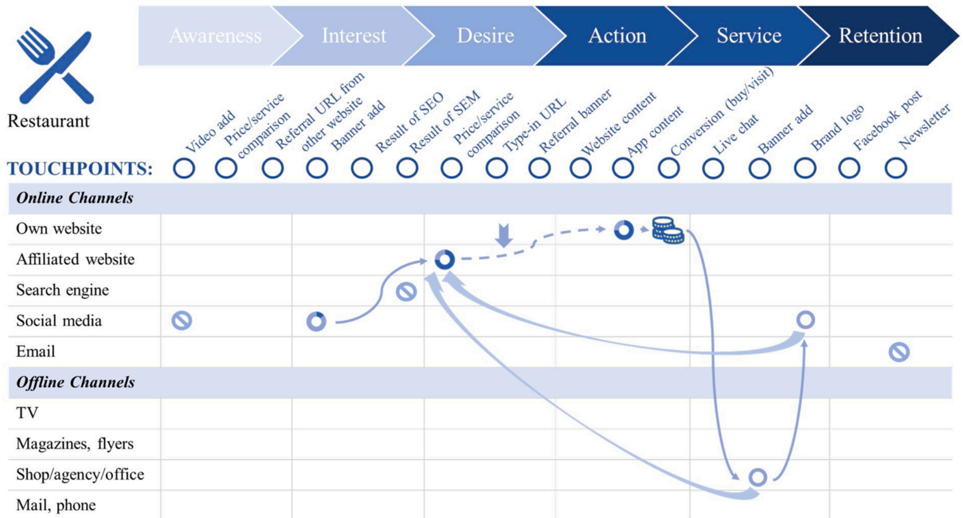

Fig. 6. Hypothesised Customer Journey for Dining.

consultations with agents as well as seeking multiple sources of information, including consulting friends and relatives (Tincher, 2014). Considering the emotional component, the impossibility of an attribution method to account for attitudinal loyalty from previous interactions or the influence of a reliable opinion (Hong & Cho, 2011), there will be an exaggeration in the perceived value of company-initiated communications.

5.2.2. Low-cost airline tickets

The search for airline tickets is generally motivated by the need to get to a defined location within a certain time period. Customers start interactions with airlines at a 'desire' stage by articulating the task to get to a certain location (Fig. 5). The customer journey often starts with exploring offers at metasearch websites (e.g. Google Flights, Kayak), Travel Agent websites or direct communication channels (e.g. phone call or online chat) or airline websites; thus, consisting of limited number of sessions along the limited range of channels. The pragmatic motives of selecting the tickets of higher comfort during a flight with minimal monetary and time investments, push them along a purchase funnel towards the ticket of a greater perceived value. As a result, a relevant offer can have sufficient effect on customer conversion (Amadeus IT Group SA, 2017).

In addition to purely utilitarian motives (price, flight comfort), purchase decisions of airline clients are also driven by relational (brand loyalty, frequent flier membership) and hedonic motives (first class of service) (Boetsch, Bieger, & Wittmer, 2011). The trend for taking several short breaks, rather than one major vacation per year, and the availability of cheap tickets to selected routes, motivate customers to start multiple interactions to explore travel opportunities. Airline tickets and holiday searches become part of the travel experience. Customers get inspiration from a range of available routes, destinations, loyalty programmes and promotions, as well as review websites or friends and family (Amadeus IT Group SA, 2017). The value can be attributed in the very early stages of the purchase funnel, when customers identify the need to travel; but are yet to define specific services they are primarily looking for (i.e. a specific route within their budget). The service in question may be researched and purchased through a range of touch points. The presence of an attractive offer can push customers to convert when that offer is exposed (Amadeus IT Group SA, 2017). Exploratory behaviour can further be interrupted by other events or motives, ending this customer journey. As a result, the range of different motives and criteria used for conversion makes the allocation of value nearly impossible.

5.2.3. Dining choice

Selection of a restaurant on a regular basis is increasingly associated with the digital environment, which has prompted the ease of accessing information and booking tables. To select a place for dining, customers often rely on metasearch and review websites, such as OpenRice and TripAdvisor (Lemon & Verhoef, 2016). Customer perceptions towards restaurants mainly depend on criteria such as food, service, environment and price (Ryu, Lee, & Gon Kim, 2012). The perception of convenience, including physical location, parking opportunities and ease of access play an additional role in decision-making (Bachman & Arigo, 2018). This also means that factors such as weather, traffic or nearby events may disrupt previous decisions (Buhalis & Sinarta, 2019). Being a social activity, choosing a dining place may be affected by other involved parties' perceptions on the abovenamed criteria. The initial touchpoints that affect the customer's decision to convert, may lose their effect in case of changes in customer context (Fig. 6).

The given examples demonstrate the importance for attribution methods to account for the factors that describe the context of decision-making and provide insights of marketing mix and the customer journey. This would include but won't be limited to the structure of marketing communications within the marketing campaign, the characteristics of the channels, the type and the content of the touchpoints, and the context of the customer at the moment, when they have been exposed to these touchpoints (Buhalis & Sinarta, 2019; Dwivedi et al., 2020). Further advancements in marketing attribution are required to guide dynamic, contextually-aware and accurate data-driven value allocation (Kannan et al., 2016; Lemon & Verhoef, 2016). Such advancements are becoming especially important with the quick proliferation of personalisation. Customer data and customer context-recognition technology align the automated and real-time adaptation of each touchpoint to the needs and preferences of individual customers, thereby, modifying customer reactions to these touchpoints. Therefore, actionable frameworks with relevant factors and their metrics are required to guide businesses in developing and selecting relevant attribution methods (Dwivedi et al., 2020; Saghiri et al., 2018).

The integration of knowledge-based and data-driven analytics advances actionable insights (Larson & Chang, 2016). Most studies attempt to incorporate the maximum amount of data possible to illustrate the complexity of customer journey (Berman, 2018). However, it has been recognised that modelling multiple complex relationships on the individual level may lead to an inaccurate value allocation, often exaggerating the role of touchpoints in costumer conversion (Nichols, 2013). Marketing attribution should have strong theoretical foundations to guide data-driven value allocation (Kannan et al., 2016; Lemon & Verhoef, 2016).

The proposed conceptual framework of marketing attribution provides such a theoretical background. The study delineated the characteristics of marketing attribution as data-driven analytics for marketing performance assessment. While the framework does not specify any parameters, it provides a holistic and multidimensional approach to explain the requirement for accurate value allocation. It guides further developments in marketing attribution methods without restricting them to standardised, context-irrelevant frameworks.

When applied together, the proposed framework, taxonomy and attribution map provide strategic tools for marketing. Taking into consideration the heterogeneity of applied terminology, the findings improve businesses' understandings about methods' capabilities both at the stage of attribution method selection as well as at the stage of accessing its efficiency and relevance. As a result, this paper provides a guide for businesses in determining possible characteristics of the models, available at the market.

Whilst the attribution vendors supply the market with a range of methods, one of the main reasons that prevent businesses from applying marketing attribution is their incapability to choose an optimal method for their case (Econsultancy, 2015, Clark, 2018; Moffett, Pilecki, & French, 2014). This study supplies businesses with a tool that allows them to identify expected properties of an attribution method and match them with the requirements for accurate value allocation. By doing this, it enables a more efficient collaboration between service providers and attribution vendors in order to develop workable custom models suitable to specific contexts.

The findings also outline the existing gaps in the attribution methods' capabilities to account for the specifics of consumer decision-making. They demonstrate the potential risks of inaccurate value allocation, arising from the limited incorporation of the specifics of customer journey in the attribution methods. Therefore, the study defines the foundations for further improvement of marketing attribution effectiveness.

6. Conclusion

This paper contrasted theoretically elaborated facilitators and the capabilities of data-driven analytics against the empirically identified classes of marketing attribution. It applied the combination of deductive and inductive reasoning to, on the one hand built on the concepts of marketing mix and the customer purchase funnel and on the other, built on secondary data. It synthesised the knowledge surrounding marketing attribution methods' facilitators and resulting capabilities to allocate value to marketing touchpoints. The original contribution of this paper is twofold.

First, the study introduced a second-order taxonomy of marketing attribution. It proposes that a marketing attribution method can be explained by five groups of parameters. The taxonomy provides a background to systematic classification of currently existing attribution methods. Second, the study demonstrated that current attribution methods do not systematically address the specifics of customer interactions with marketing mix and transition along the purchase funnel. This potentially compromises the accuracy of value allocation. Supplemented by the proposed conceptual framework and map, it has created a novel theoretical background for advancing attribution methods towards a holistic customer-decision-driven approach.

The findings advance the knowledge in the domain of marketing performance analytics. They help build a bridge between the research on consumer behaviour and customer journey analytics, thereby, creating a theoretical background for cohesive development in the domain of marketing performance measurement. However, the proposed taxonomy and map have two major limitations. According to the definition, a taxonomy represents existing phenomena through mutually exclusive classes (Nickerson et al., 2013). The qualitative content analysis does not eliminate a partial overlap in the classes of cross-digital, cross-channel and cross-platform attribution. Therefore, the proposed taxonomy cannot support a fully exclusive allocation to one of those methods. Moreover, the analysis only incorporates only currently already described and explained methods, potentially missing unannounced alternatives. Considering the developing nature of attribution, it is likely that the number of diverse approaches will increase over time. Taxonomies, as tools for classification, are also only relatively steady structures and tend to evolve over time (Nickerson et al., 2013). Future research will review the changes that will occur in the market of attribution methods to keep the findings relevant for research and decision-making. It will further explore the opportunity to introduce the third-order classes of methods, which will eliminate any existing overlap in the meanings.

Appendix A

Table A1
Definitions of the Key Concepts.

Concept	Definition	Examples
Marketing Communication	A message, designed in the form of a specific type of media	A static banner, video, text message, email, face-to-face voice conversation
Marketing Communication and Distribution Channel (Marketing Channel)	A specific way to transfer information and goods between a customer and a service provider	Product website, search engines, email services, social media, online chats, shops, billboards, phones, people
Marketing Touchpoint	An interaction between a customer and a brand, experienced by the customer via a marketing communication and distribution channel in the form of a marketing communication	A banner of the website, a result of information search, a direct email
Conversion	An action that a service provider wants customers to perform	Online purchase, reservation, offline shop visit, download of a brochure, decision to visit a destination
Marketing Performance Measurement	An assessment of the effectiveness of marketing communications and the efficiency of marketing investments	Assessment of the whole scope of communications, assessment of a specific marketing campaign
Marketing Attribution	The strategy of allocating the value of marketing communications to the identified marketing touchpoints exposed to consumers along customer journeys	Single-touch, multi-touch, U-shape, rule-base

Appendix B

Table B1
Reviewed publications.

	Peer-reviewed journal papers	Conference papers and proceedings	Business reports	White papers
Introduce Attribution Analytical Frameworks, Methods and Modelling Techniques	Tucker (2013), de Haan et al. (2016) ; Anderl, Becker et al. (2016); Li and Kannan (2014) ; Xu et al. (2014), Kireyev et al. (2016); Ghose and Todri (2015), Naik and Peters (2009); Nottorf (2014), Wiesel et al. (2011), Wooff and Anderson (2015), Lee (2010), Mukherjee and Jansen (2017) , Kakalejčík, Bucko, Resende, and Ferencova (2018); Wedel and Kannan (2016)	Jordan, Mahdian, Vassilvitskii, and Vee (2011); Dalessandro, Perlich, Stitelman, and Provost (2012); Shao and Li (2011); Abhishek et al. (2012); Berman (2018); Geyik et al. (2015); White et al. (2014); Hou et al. (2016); Sinha, Mehta et al. (2015); Yadagiri et al. (2015); Yin, Li, Mazzoleni, and Shen (2016); Sinha, Saini et al. (2015); Barajas et al. (2012); Ji, Wang, and Zhang (2016), Zhang et al. (2014), Arava, Dong, Yan, & Pani (2018)		
Include Reviews and Conceptualisations of Marketing Attribution	Anderl, Schumann et al. (2016); Kannan and Li (2017); Bucklin and Sismeiro (2009); Ailawadi and Farris (2017); Ansari, Mela, and Neslin (2008); Kannan et al. (2016), Wiesel et al. (2011), Anderl, Becker, von Wangenheim, and Schumann (2013); Barger and Labrecque (2013) ; Hosseini et al. (2018) ; Hülsdau and Teuteberg (2018); Saghiri et al. (2018)		Raab (2011); Nichols (2013); Lovett (2009); Moffett (2014); Moffett, Pilecki, McAdams et al. (2014), 2014a; Eichmann (2014), Visual (2018); Econsultancy (2015), 2012; Forrester Research (2016), 2014; Econsultancy (2017)	Branch (2018), Rakuten Marketing (2015), Adometry by Google (2014), Adobe Systems Incorporated (2014), Bates (2014), Krainik (2014), Adobe Analytics (2018)

Appendix C. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ijinfomgt.2020.102253.

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