Improving Consulting Processes in Web Analytics: A Framework for Multichannel Analytics

Full paper

Yves Studer
University of Applied Sciences
Northwestern Switzerland
University of Camerino
yves.studer@gmail.com

Uwe Leimstoll
University of Applied Sciences
Northwestern Switzerland
Institute for Information Systems
uwe.leimstoll@fhnw.ch

Abstract

To control and optimise their marketing activities, organisations analyse customer behaviour on their online and offline channels. This is referred to as multichannel analytics (MCA). As enterprises often do not have the necessary know-how to implement analytics processes, analytics consultants support them in such projects. The problem for the consultants is that a standardised approach, which provides orientation and guidance during such projects, is currently not available. The goal of this paper is to develop a framework, which guides consultants in order to avoid common project-related problems. It is developed employing Design Science Research Methodology. Empirical data collection and iterative validation of the framework are based on literature research, document analysis, expert interviews and a focus group. Results highlight that it is useful to combine a capability maturity model and an analytics procedure model. This allows taking into account the different degrees of organisational maturity during the consulting process.

Keywords

Multichannel Analytics, Procedure Model, Maturity Model, Business Analytics, Business Intelligence

Introduction

As companies seek to optimise their marketing activities, they aspire to gain insights through the analysis of customer activities on online and offline channels, referred to as multichannel analytics (MCA). Analytics consultants often support organisations in such projects with the objective to improve analytical processes based on their specialised expertise. Interviews with such consultants conducted at the beginning of this study show that there is a need for a procedure model, which provides orientation and guidance to them. However, of the existing models, partially incorporating MCA aspects, none has been found to entail a procedure model for the integrated support of practitioners or analytics consultants. Furthermore, several possibilities for integrating online and offline data exist but these are only part of a few models analysed (specifically Arikan 2008). Thus the motivation and goal of this paper is to fill this gap and develop an artefact called the Multichannel Analytics Framework (MCAF).

The main research question is: How has a framework to be designed in order to guide analytics consultants through the process of setting up MCA projects, helping them to avoid known project-related problems? To find a suitable solution, the developed framework considers requirements derived from common problems identified in completed analytics projects. An iterative development and evaluation process ensures that the final version of the framework meets the practical requirements.

The next section of this paper clarifies essential terms and gives a short overview of related literature in relevant fields. Subsequent sections highlight the research method and the development process of the MCA framework. The last section summarises the results and draws conclusions.

Literature Review

This section defines and delimits MCA from adjacent domains. Furthermore, it discusses recent developments, analyses existing analytics frameworks and maturity models.

Cross-, Omni- or Multichannel Analytics?

A wide range of buzzwords, different definitions and heterogeneous use of terms was experienced during the literature research process in the area of web analytics, business intelligence, big data, etc.

"Crosschannel", "omnichannel" and multichannel" can be described as buzzwords and are often used interchangeably (Arikan 2008). Common with all these terms is that they relate to the combination of different sales forms. More specifically, the terms have different meanings as Arikan (2008) exemplifies. He defines **cross-channel** as "the act of beginning a communication, or buying cycle, on one channel and *crossing* into another channel to continue it there". Heinemann (2013) describes **omnichannel** as a trend related to consumer behaviour: The consumer uses media and transaction channels simultaneously. From Heinemann's perspective, it is *not* a retailing strategy but a phenomenon, which is describing change in consumer behaviour based on technological advances. This corresponds to the view of Brynjolfsson et al. (2013) who remark that advances in technology are "merging touch-and-feel information in the physical world with online content" which they name "omnichannel environment". Arikan (2008) sees a **multichannel** business as "one that interacts with its customers through multiple media—for example, through a telephone, store, and website." Arikan (2008) as well as Heinemann (2013) highlight that nearly all businesses today are in fact multichannel businesses. For Arikan (2008) multichannel *marketing* relates to "marketing communications delivered on multiple media in parallel and, hopefully, in a coordinated fashion. The term also implies that responses to marketing initiatives are accepted from multiple channels".

Kaushik (2010) names **multichannel** marketing as one of the "most underappreciated and difficult things to measure" by (web) analytics. So why should one conduct multichannel analytics for marketing? Arikan (2008) discusses occurring problems when *no* multichannel analytics for marketing is employed:

- "Marketing accountability remains an empty wish because marketing results that play out across a fragmented landscape of channels cannot be consolidated.

- Integrated marketing communications cannot be allocated to channels optimally because the effectiveness of each channel is not understood.

- Customer-centric marketing strategies remain off target because the picture of the customer is torn into multiple pieces where interactions cross channels.

- The value of viral and Web 2.0 marketing strategies cannot be evaluated because they are multichannel campaigns by nature."

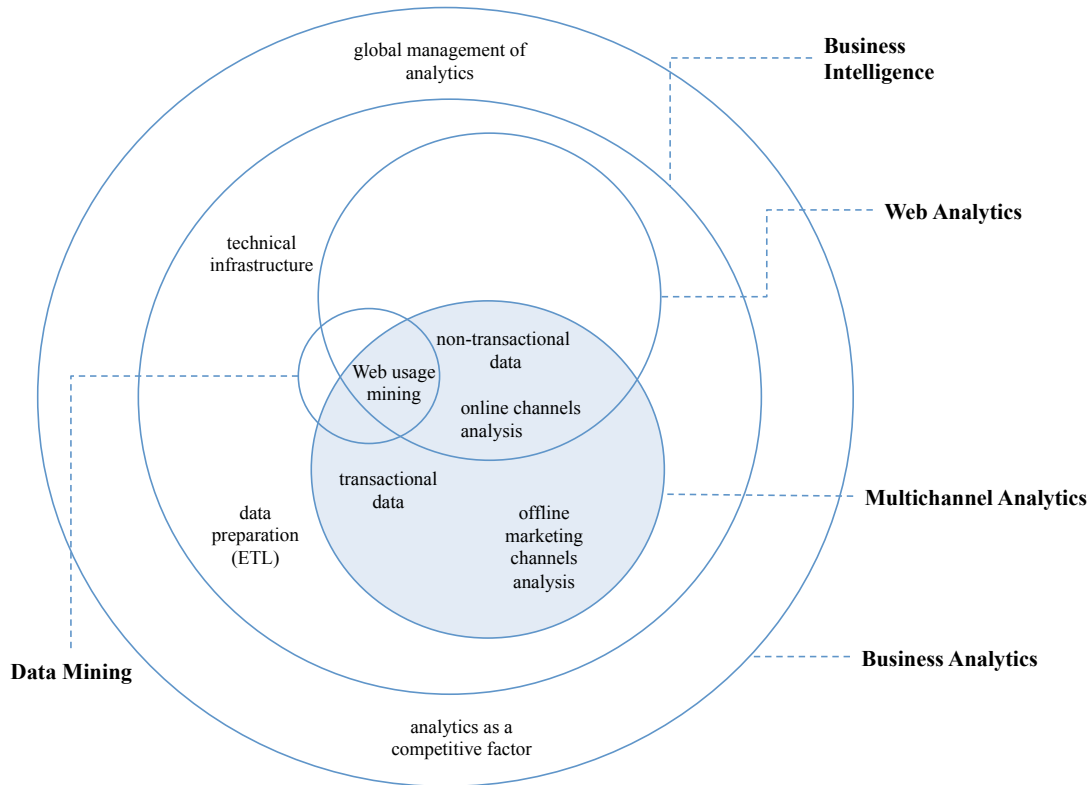Figure 1 visualises the classification of MCA within adjacent domains.

Figure 1: Multichannel analytics and adjacent domains. Source: own illustration

Davenport and Harris (2007) describe analytics as a subset of business intelligence (BI) rather than a substitution of BI. Sheikh (2013) also remarks that the attempt of replacing BI by analytics is counterproductive: for him BI has more of a historical perspective ("what has happened?"), whether analytics has predictive elements ("What can happen?").

This paper expands web analytics and therefore uses the term multichannel analytics to account for the new variety of marketing channels and especially the combination of online and offline data. As web analytics can be described as a subset of business intelligence, MCA can be considered as a subset of BI as well.

Definition of Multichannel Analytics (MCA)

Based on the definitions of Sheikh (2013), Kaushik (2010) and Davenport and Harris (2007), MCA can be defined as follows: Multichannel analytics are the processes, the technologies and the organisational aspects in which data are collected across various online and offline marketing channels. Furthermore, MCA considers how these data are converted into information, how they transcend into knowledge, how that knowledge is used to reach human or automated decisions, and how those decisions are constantly evaluated and improved.

Recent Developments

Recently emerged communication channels such as mobile and social media widened the scope of web analytics. Furthermore, an increasing amount of offline activities are now being "digitally recorded" as the OECD (2013) states in their policy-related report on big data. Also, as online and offline channels converge, more channels are changing from non-addressable marketing channels to addressable ones (Arikan 2008). The impact online marketing campaigns have on the customer in an "offline"- or "noline"-setting (Kaushik 2010, p. 294) is of particular interest in MCA for marketing purposes.

Combining offline and online information

Beyond comparing the behaviour of aggregates such as user segments, personalised marketing needs an anonymous yet specific user profile. However, a main challenge in combining offline and online data is to find a common denominator for identifying the user such as a unique identifier (ID) or aggregated profiles for user identification in order to allow for personalisation, product recommendation, fraud detection etc. (Yang 2010).

An example of combining offline and online analytics is the behaviour analysis of a customer seeking information online through search engines and his subsequent purchasing behaviour in a store (Panda 2013). **Behaviour-based user identification** is losing accuracy as many users could share similar behavioural patterns but different interests (Yang 2010). Therefore targeted marketing is difficult to achieve. The academic body of knowledge for "offline analytics" is somewhat sparse. Wakolbinger (2009) and Evans (2013) focus on the differences between online and offline advertising. Feit & Wang (2013) outline a technical method (Bayesian data-fusion) to separate the intraday correlations of different media channels for later analysis. They also outline strategies on how to use this method for measuring the interplay of offline and online purchasing behaviour. Schijns (2012) analysed the behaviour of consumers which informed themselves over different offline- and online channels until making the transaction on the same or another channel and derived "shopper archetypes".

Despite the low academic recall, several practitioners (Arikan 2008; Burby and Atchison 2007; Clifton 2012; Hassler 2012; Kaushik 2010; Schwarz 2008) have listed obstacles for this topic and according strategies to overcome them. Possible solutions for combining online with offline media include vanity URLs (Clifton 2012; Hassler 2012; Kaushik 2010), hashtags, comparing traffic patterns with other analysed channels (Kaushik 2010), specific phone numbers, quick response (QR) codes, physical tokens such as coupons, mobile phones e.g. by using NFC or RFID capabilities, biometrical identifiers (Yang 2010), registration / login, incentives such as wish lists or access to individual recommendations of products or services through a recommendation engine (Yang 2010).

Existing Analytics Frameworks

Frameworks and maturity models in adjacent domains are mostly closed-loop models. All models are indifferent of specific analytics software but each model is focusing on different aspects of analytics. However, during the conduct of this research, no framework that guides analytics consultants during MCA projects could be found.

Waisberg and Kaushik (2009a) described a web analytics process, which consists of the steps "defining goals, building key performance indicators, collecting data, analysing data and implement changes". Here, only data analysis and the implementation of changes are iterative. This process was reused in several publications analysed.

Amthor and Brommund (2010) describe an analytics framework which is relying on a full control-circuit: The phases planning, measurement, analysis and optimisation are the key practices. These stages can be seen as key practices for MCA as well. They also describe an organisational positioning of analytics within an organisation.

De Oliveira and Laurindo (2011) argue that many problems in analytics projects occur because of a too narrow, technical or tool-related focus and lower effort on conceptualisation of analyses. Thus, they propose a framework for a better understanding of the customer relationship.

Peterson (2009) advocates an array of activities for initiating a web analytics programme which range from developing a roadmap to iteration and improvement.

Chaffey and Patron (2012) argue to achieve an increased adoption-rate of web analytics, a repositioning as improvement process such as 'digital marketing optimization' is important. They describe a framework for optimising online marketing performance including the steps "reach, act, convert, engage". While, their framework is not comprehensive and lacks organisational aspects, it can be used as a method for customer lifecycle analysis.

Davenport and Kim (2013) investigate analytical thinking itself. No other analytical framework analysed did involve the communication of results to management and an emphasis on acting on analytical outcomes. The model can be considered for the actual decision-making process within MCA as it the described activities are generic.

Saxena and Srinivasan (2013) use analytics from a BI-perspective: the alignment of the organisational domain where decisions are made and the support of this decision-making process in the analytics domain. Whereas the BI-perspective is out of scope for this paper, the analytical phases can also be considered for MCA. They also provide a process structure for decision-making.

Sheikh (2013) provides detailed information on the design, implementation, organisation and governance of an analytics solution. His analytics project lifecycle includes the stages requirements, analysis, implementation, deployment, audit and control.

All described approaches are based on the paradigm that stages or activities are executed sequentially in a waterfall-like process. However, there are approaches for analytics project management, which draw on agile principles, e.g. Collier (2012) who covers continuous integration for analytics purposes.

Existing Maturity Models in Analytics

Focusing on analytical activities, analytics consultants assess the current state of the analytical processes and infrastructure and then aim to (continuously) improve the analytical capability of the organisation. The organisation in turn expects at least a positive Return on Investment (ROI) thanks to these activities (Hamel 2009). Analytics projects can be regarded as process improvement of an organisation as the analysed existing analytics maturity models show.

Maturity models for business performance management (BPM) aim to support the selection of an appropriate improvement strategy by determining the current process maturity and identifying the most critical issues for improving quality and process (Paulk, M.C., Curtis, B., Chrissis 1993). Many of such maturity models have been influenced by Capability Maturity Model Integration (CMMI), see Bruin et al. (2005). Davenport et al. (2010) compared their business analytics maturity model with CMMI. Analogous to software development, they adapted it especially for business analytics to describe what an organisation should do from a very early stage (i.e. a company with virtually no analytics) to being a "serious analytical competitor" (Davenport & Harris 2007). This was the reason for Davenport et al. (2010) to introduce an analytics maturity model covering an overall business perspective. Even though the model is cited often, a detailed assessment methodology cannot be found and thus, assessing the capability is only possible on a broad level.

Despite providing organisational guidance for reaching an increased maturity, Hamel (2009) also critically reflects on such models. In his opinion, negative aspects are the lack of a "formal theoretical basis", "vague empirical support" and the deviation of an organisation's true goals in order to just achieve a next maturity level. Notwithstanding, he sees benefits of maturity models overweigh as they provide tools to perform an assessment of the as-is state and guidance for the to-be state. Furthermore, he sees maturity models to improve internal communication and have an impact on management acceptance.

Cosic et al. (2012) propose four capability areas of business analytics and attach for each of these areas another four subordinate "low level capabilities", which should be assessed. While some of the low level BA capabilities described are also valid for MCA, they are too generic and lack detailed assessment criteria.

Hamel (2009) proposes a Maturity Model for Web Analytics (WAMM). It is structurally similar to CMMI as it uses six key process areas and assesses the maturity of the organisation from six maturity levels. However, he uses a simplified terminology for goals, focuses on the continuous representation and names stages "maturity levels", not "capability levels" as CMMI does.

Saxena and Srinivasan (2013) propose an Analytics Maturity Model with three dimensions: capability, culture and technology . This is similar to the three "capabilities" organisation, human and technology seen above from Davenport & Harris (2007).

From their research findings and the existing CMMI, Tan et al. (2011) propose the Enterprise Business Intelligence Maturity Model. Its main goal is to allow an assessment of the current state of BI capabilities,

identify weaknesses and improvement strategies. As most maturity models analysed, five levels of maturity are distinguished. These are combined with four dimensions, which are specific to BI. The dimension "analytics" is identical to the stages suggested by Davenport and Harris (2007), but lacking detailed practices and descriptions. Thus, except the importance of underlying information quality, it adds no additional value for MCA.

Subconclusion

The literature review reveals that there are several existing frameworks and models including methods and organisational aspects for web analytics, business analytics as well as business intelligence developed by both scholars and practitioners. It was identified that organisational maturity is used as an influencing factor for analytics, shaping the activities contained in models analysed. Even though most maturity models are based on CMMI, they lack a clear assessment method for assigning maturity levels. Of the models, which partially incorporated MCA aspects, none was found to entail a procedure model for the integrated support of practitioners or analytics consultants. Furthermore, there exist several possibilities for integrating online and offline data but these are only part of a few models analysed.

Research Method

For the design of the MCAF, the Design Science Research Methodology (DSRM) presented by Peffers et al. (2007) is selected and combined with the Design Science Research (DSR) guidelines suggested by Hevner et al. (2004). The sequence and methods used can be found in Figure 2. Design Science Research helps to solve practical problems using IT-related artefacts. In particular, it allows iterations in the development process of the artefacts and a validation phase ensures the rigour of the results. It has already been applied specifically for the purpose of framework development in previous research (Hevner et al. 2004; Österle et al. 2010).

The MCA framework is developed using a problem-based approach: Once a set of common problems in analytics projects is established, requirements of the framework are derived including goals, which the framework addresses directly. The results of the literature research disclose that a simplified structure of CMMI (the de-facto standard for maturity models) and the WAMM from Hamel (2009) (itself being derived from CMMI) seem to be the best basis for the development of the new artefact.

The design cycle was used three times and the artefact extended iteratively. For conciseness reasons, only the final iteration is described in this paper. The DSRM was supported by the means of literature review with literature ranging from 2007 to 2014, artefact analysis (document analysis of completed projects from 2007 until 2014) and six semi-structured qualitative expert interviews during March and April 2014. The experts' experience in analytics ranges from a minimum of two, to a maximum of twelve years. The interviews were all audio-recorded and summarising transcripts were generated based on the audio recordings. Subsequently, an inductive approach is used: Every interview goal was analysed using the interview notes and iteratively tagged with identified categories adding to a conceptual framework as the interviews progressed. This can also be regarded as a "grounded approach" according to Saunders et al. (2012, p. 549).
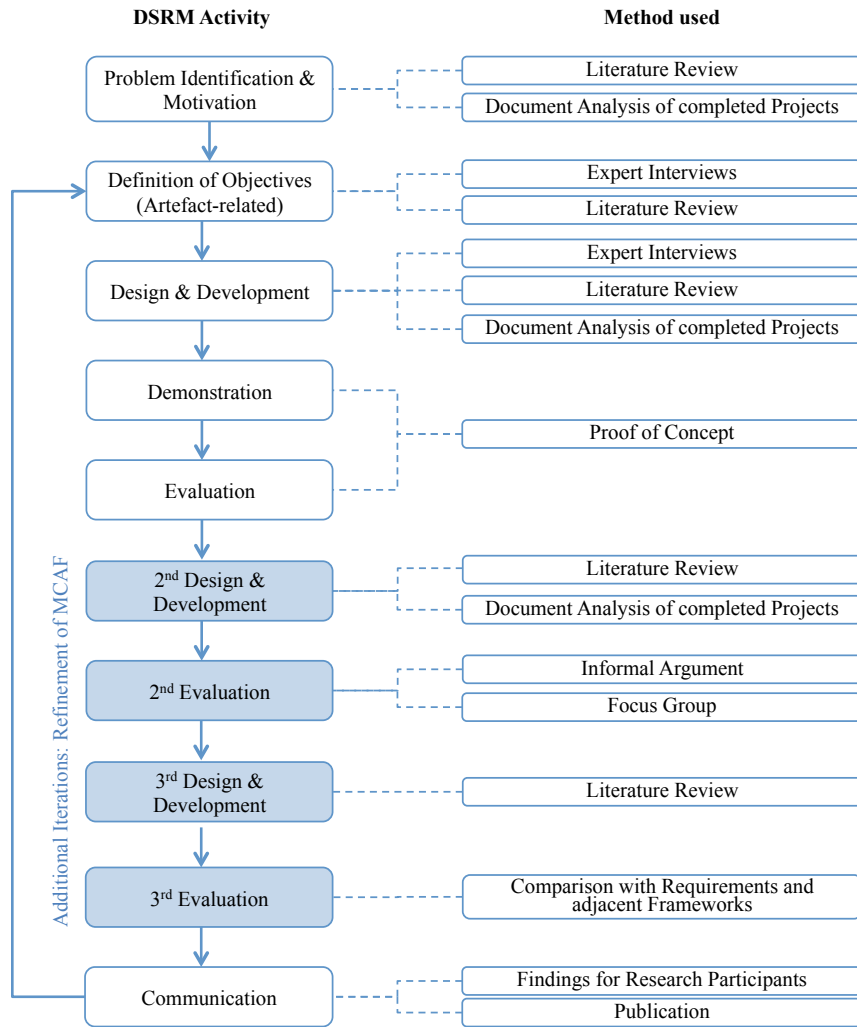
Figure 2: Design Science Research Methodology (DSRM) by Peffers et al. (2007), extended by methods during research.

The artefact was evaluated in terms of quality, utility and efficacy (according to Hevner et al. 2004). The first evaluation cycle consisted of a proof of concept (post-project implementation). Secondly, an expert focus group consisting of four analytics consultants in May 2014 was conducted. Barnett (2002) states that researchers often disagree about the proper number of participants for a successful focus group. She compared six scholars, where proposed participant numbers ranged from four to twelve. In her opinion, what is more important is striking a balance between "having a lively discussion" and the "danger of overwhelming group size" than the actual number of participants (Barnett 2002). It was considered to choose analytics consultants who are from two categories: novices (analytics experience from two to three years) and advanced (three to five years), as the framework is aimed at both.

Thirdly, the findings shape the final framework, which is assessed with the initially derived requirements and adjacent frameworks. Additionally the DSR guidelines by Hevner et al. (2004) served as an evaluation catalogue for the final artefact from a method-related point of view.

Developing the Multichannel Analytics Framework

First, before the actual development of the framework starts, meta-goals, problems and requirements are identified. The meta-goals determine the aim of the framework itself and serve as a guideline for the overall development. Subsequently, problems in analytics projects are summarised from literature review, expert interviews and a document analysis. From these problems, a set of requirements for the framework is derived in order to achieve relevance for the target group analytics consultants. This step can be compared with the "relevance cycle" of Hevner & Chatterjee (2010).

Secondly, structural elements are established and modelled using a meta-model. It states that organisational maturity is defined by fulfilled groups of components, so called key process areas (KPA). KPA are specified by a set of sub-components called key practices (KP). Each KP in turn requires at least one result. Roles are used to determine what type of individual conducts a KP. Then, this meta-model is instantiated by actual content-related components resulting in the first version of the MCAF. It consists of five maturity levels (ML), 21 goals, which directly address requirements, seven KPA and 28 KP including according results and roles.

Meta-Goals of the MCAF

The second step in the DSR method applied is to determine goals of the artefact to be designed (i.e. meta-goals since it relates to the goals achieved by using the MCAF itself). Consolidating the results from expert interviews, the main goal is that the framework supports consultants by attaining the meta-goals outlined. These meta-goals (MG) served as design-constraints for the development phase:

- MG1   The framework is concise
- MG2   The framework supports the standardisation of analytics projects
- MG3   The framework can be used by beginners and more advanced consultants
- MG4   The framework incorporates a process flow in order to guide consultants

Deriving requirements and goals from existing problems in Analytics

The problems identified during literature review, expert interviews and document analysis were then translated into requirements and goals for the MCAF (see corresponding columns in Table 1).

Problem	Sources from Literature Review						Expert interviews	Document Analysis	Derived MCAF Requirements	Derived MCAF Meta-Goal (MG) / Goal (G)
	Burby & Atchison (2007)	Greco (2014)	De Oliveira & Laurindo (2011)	Kaushik & Waisberg (2009)	Peterson (2009)	Zumstein (2012)				
Process / method-ology flaws	✓				✓		✓	✓	Must incorporate process flows and methodical elements	MG4: MCAF incorporates a process flow in order to guide consultants G4: All involved individuals are aware of their roles and responsibilities

Problem	Sources from Literature Review						Expert interviews	Document Analysis	Derived MCAF Requirements	Derived MCAF Meta-Goal (MG) / Goal (G)
	Burby & Atchison (2007)	Greco (2014)	De Oliveira & Laurindo (2011)	Kaushik & Waisberg (2009)	Peterson (2009)	Zumstein (2012)				
Definition of KPIs / metrics	✓	✓		✓		✓			Must include methodical elements for KPI development	G3: Business goals are quantified using KPIs
Data quality issues	✓		✓			✓	✓		Must include practice for data quality assurance	G11: The data serving as an input for the analytics solution is suitable for business decisions
Data overload	✓								Should include prioritisation of data to be analysed	G7: Prioritised activities are planned using an analytics roadmap Additionally addressed in Key Practice: Prioritise activities
Value / monetisation problems	✓		✓	✓			✓		Must ensure that qualitative and quantitative business goals are met in order to solve value / monetisation problems	G2: Areas in MCA, which generate value (business goals) are known to all stakeholders. Additionally addressed in ensuing Key Practice: Act on learning and communicate achieved business value)
Prioritisation *problems*	✓						✓		Should include prioritisation of data sources and MCA activities	G7: Prioritised activities are planned using an analytics roadmap
Access to data sources	✓							✓	Should inform on early access validation of data sources in order to secure access to data sources needed	G8: Suitable data sources are selected. Additionally in Key Practice: Set up and integrate data sources
Unclear Scope	✓			✓			✓		Must entail methods for scoping and planning with business users to achieve clear scope and business requirements	G5: Current and possible future marketing and MCA activities are outlined

Problem	Sources from Literature Review						Expert interviews	Document Analysis	Derived MCAF Requirements	Derived MCAF Meta-Goal (MG) / Goal (G)
	Burby & Atchison (2007)	Greco (2014)	De Oliveira & Laurindo (2011)	Kaushik & Waisberg (2009)	Peterson (2009)	Zumstein (2012)				
Incorrect business Requirements	✓		✓	✓	✓		✓		Must entail methods for scoping and planning with business users	G1: MCA activities are aligned with business needs
No link between business goals and KPIs	✓	✓		✓					Must incorporate method for linking business goals to KPIs	G3: Business goals are quantified using KPIs
Not actionable outcomes	✓			✓		✓	✓		Must suggest and prioritise actions in terms of business value and feasibility in order to be more actionable	G12: The analytics tools provided are being used. G13: Decisions are made on the basis of information provided by the analytics solution. G15: Insights from the analytics solution are applied into actions
Executive Support	✓		✓	✓	✓		✓		Must analyse & involve stakeholders in planning Must entail methods for scoping and planning with business users in order to achieve clear scope and business requirements	G4: All involved individuals are aware of their roles and responsibilities. G2: Areas in MCA analytics, which generate value (business goals) are known to all stakeholders
Analyst know-how and commitment	✓		✓		✓	✓	✓		Should incorporate practices for novices / should consider the current analyst know-how in maturity assessment	MG3: The framework can be used by beginners and more advanced consultants

Problem	Sources from Literature Review						Expert interviews	Document Analysis	Derived MCAF Requirements	Derived MCAF Meta-Goal (MG) / Goal (G)
	Burby & Atchison (2007)	Greco (2014)	De Oliveira & Laurindo (2011)	Kaushik & Waisberg (2009)	Peterson (2009)	Zumstein (2012)				
Interpretation of data						✓			Should outline methods, which improve the interpretation of data	G10: The analytics solution facilitates business insight. G16: The performance of relevant marketing channels is known
Lack of standardisation in data collection methods						✓		✓	Should outline possibilities for standardisation in data collection and data integration	G8: Suitable data sources are selected G21: Testing is automated
Integration issues (technical and online / offline)	✓	✓			✓	✓			Should outline possibilities for standardisation in data collection and data integration	G8: Suitable data sources are selected
Privacy and data protection issues						✓	✓		Must consider privacy and data protection issues	G17: The customer profiling is based on data collected, not assumed personas. G18: Personalisation is used in marketing activities G20: Predictive modelling is used for customer profiling
Lack of time or budget					✓	✓			Must incorporate a mutually defined roadmap/plan	G7: Prioritised activities are planned using an analytics roadmap
Inter-disciplinary collaboration						✓			Must involve several domains from the early beginning and define team and responsibilities	Addressed in Key practice: Identify stakeholders and define target group(s)
Lack of required feature in analytics software			✓						Should assess capabilities of analytics software and agree on requirements for the software evaluation	G9: The analytics software is assessed / evaluated using business requirements

Problem	Sources from Literature Review						Expert interviews	Document Analysis	Derived MCAF Requirements	Derived MCAF Meta-Goal (MG) / Goal (G)
	Burby & Atchison (2007)	Greco (2014)	De Oliveira & Laurindo (2011)	Kaushik & Waisberg (2009)	Peterson (2009)	Zumstein (2012)				
Limitation to quantitative information		✓							Should take into account qualitative information	G19: Qualitative information and benchmarking are enhancing insights

Table 1: Identified problems in analytics projects by source and derived requirements as well as goals for the MCAF. Sources: literature review, expert interviews and document analysis, own work.

Meta-Model: M1 model of the MCAF

In order to achieve a clear structure of the framework, a M1 model according to the Meta Object Facility (MOF) meta-modelling architecture is designed (see Figure 3).
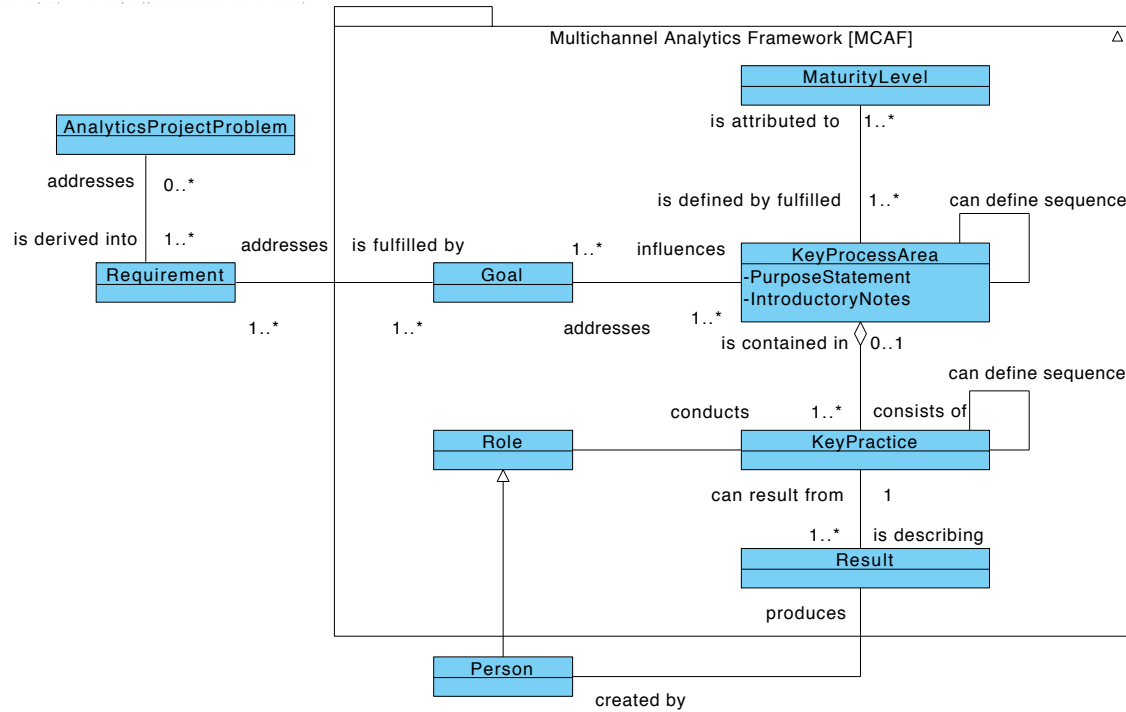

Figure 3: First iteration of the MCAF model (on MOF level M1) modelled as class diagram using UML 2.0. Source: Own work

Subsequently, the maturity levels and key process areas are outlined. Due to space constraints, the key process areas, including their 27 key practices are named only. Detailed descriptions and attributed exemplary results as well as corresponding roles were also derived but are not part of this paper for the same reason.

Maturity Levels

Based on the analysed problems, maturity levels are derived. Table 2 depicts the designed maturity levels.

Maturity Level (ML)	Description / Assessment Criteria
ML 0: Impaired	There are some analytics projects but the *business value is unclear* to management.
ML 1: Initiated	Uses analytics for *monitoring one online channel*, e.g. the website.
ML 2: Integrated	Uses analytics for *monitoring multiple online channels*, e.g. the website and social media. It uses disparate dashboards.
ML 3: Tactic	Has an integrated dashboard and uses analytics to *test marketing campaigns and adapt* them accordingly.
ML 4: Strategic	Uses *multichannel analytics* across multiple *online- and offline channels* and *optimises marketing decisions* beyond campaigns, e.g. for brand awareness.
ML 5: Automated	Uses analytics *across multiple online and offline channels and optimises some areas of marketing automatically*.

Table 2: Overview of designed maturity levels (iteration 1). Source: Own research

Guiding the Analytics Consultant – Procedural Steps

The first part of the MCAF gives an overview of the MCA project cycle. Formally, it is modelled using tasks and sub-processes in BPMN. A task corresponds to a KP and a sub-process corresponds to a KPA from the M1 meta-model. Also included in the overview are three important KP: They are executed before the start of the project or iteration (preceding KP 0.1) and after iteration, respectively when the project is stopped due to an external event (ensuing KP 0.2 respectively ensuing KP 0.3).

The diagram depicted in Figure 4 shows that once a project is initiated, the MCA process cycle starts and the analytics consultant is guided through all necessary steps in a loop. Most KPA should only be executed if the organisation has a certain ML to ensure that perquisites for the KP of a KPA are established. A maturity assessment (KP 0.1, "Assess Maturity Level") ensures that the ML is known before the process starts. Whenever all activities of a certain KPA are completed, the KP 0.2 "Act on learning and communicate achieved business value" is executed and the process is iterated. Obviously, certain KP can be skipped if they are aligned with the insights generated, as the model is intended as a means to an end: The aim is flexible guidance, not strict enforcement of certain activities. However, it is important that the analytics consultant reviews the completed results as this ensures that the overall analytics project is still aligned with business needs and is drawing from the insights and learning gained. There are detailed descriptions of each KPA or KP including roles and results but due to space constraints they are not part of this paper.
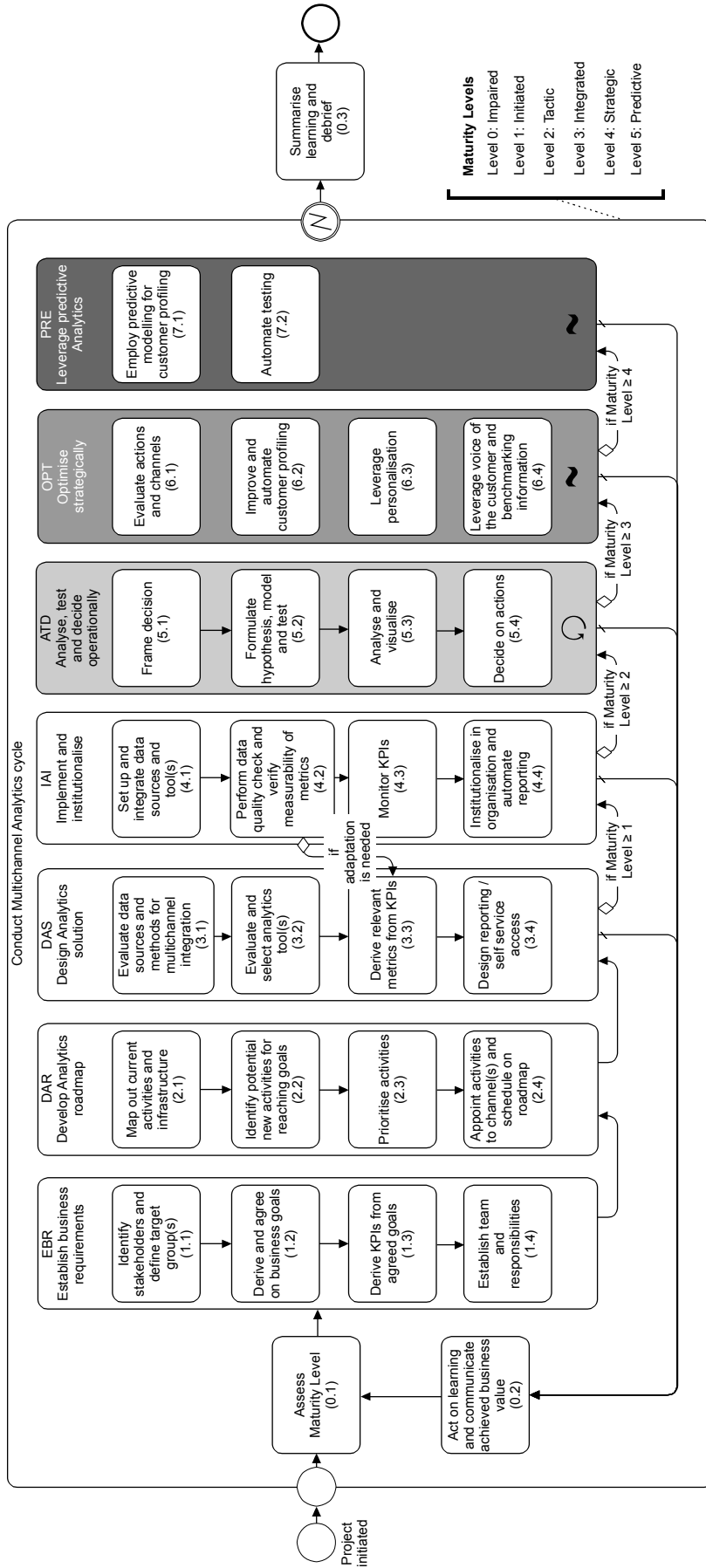
Figure 4: Third and final iteration of MCAF formally modelled in BPMN with expanded sub-processes (=Key Process Areas) revealing their tasks (= Key Practices). Source: Own illustration

For presenting the model to stakeholders with limited knowledge of BPMN, such as clients of analytics consultants, a simplified version of this high-level overview can be used which is depicted in Figure 5. Several elements such as KP 0.3, conditions and loops are omitted here to focus on the basics. The figure highlights that the process is a) shaped by maturity levels of the organisation and b) of iterative type. Furthermore, all KPA are listed to give the stakeholder orientation before or during the project.
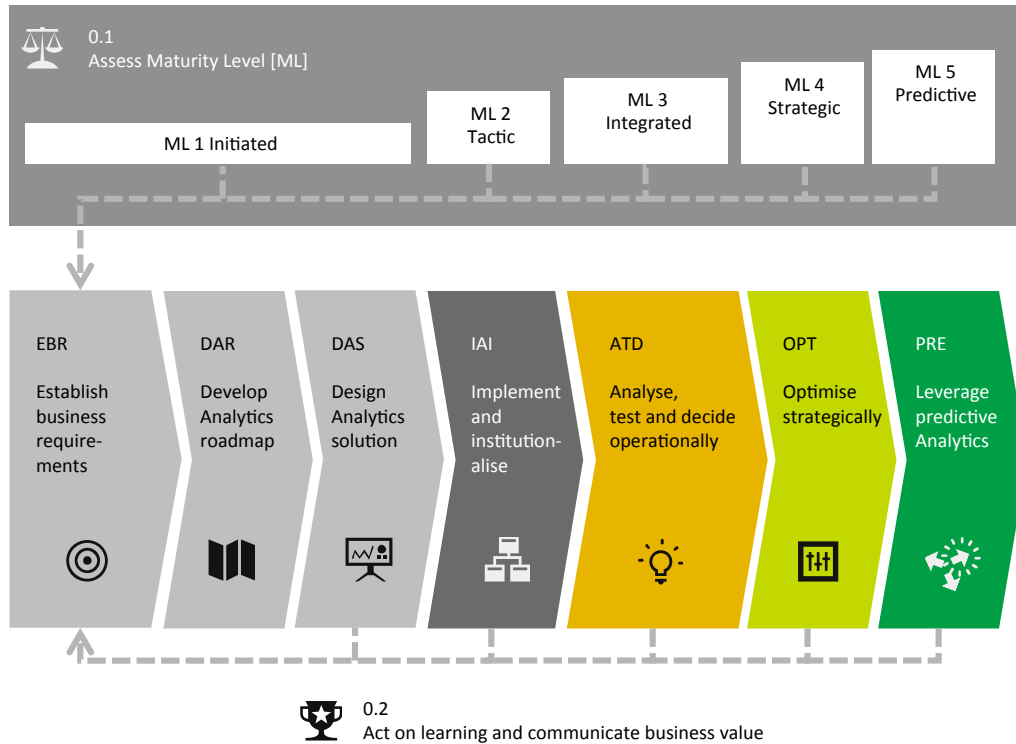

Figure 5: Third and final iteration of the MCAF's high-level Key Process Areas overview including maturity levels (informal). Source: Own illustration

Conclusion

The goal of this paper was to develop a framework that guides multichannel analytics consultants through projects of introducing analytics processes and tools in organisations. The development of the framework follows the Design Science Research Methodology and comprises three cycles of iterative design, evaluation and improvement. Empirical data stems from document analyses and interviews as well as a focus group conducted with analytics consultants.

During the first *design* cycle, it has become clear that MCA activities depend on the maturity of the organisation they are conducted in. For this reason, the MCAF is based on the CMMI maturity model and challenged with Hamel's (2009) Web Analytics Maturity Model in order to consider these organisational maturity aspects. The full framework includes a criteria-based assessment methodology, which helps to assign a company to the respective maturity level. The combination of these models and methodologies is unique in web analytics. Other models, which partially incorporate MCA aspects, do not entail a procedure model for the integrated support of analytics consultants. The second design cycle added one additional key practice (KP 2.2) and extended another (KP 4.2). The third adapted naming and lead to the introductions of checklists.

The first *evaluation* cycle revealed that the framework is implementable through a proof of concept (post-project implementation). In the second evaluation cycle, the focus group unanimously judged it as

applicable and helpful in practice for use as guiding reference for analytics consultants. Furthermore, it was identified that the framework helps companies to assess their maturity level for MCA and that it can be used as a roadmap on their journey to more sophisticated multichannel analytics. Additionally, it can be employed to structure gained knowledge and share it with the organisation. The third evaluation cycle assessed it with the initially derived requirements where 18 of 19 requirements were fully fulfilled and one (standardisation for data collection and integration) was partially fulfilled. Furthermore, all meta-goals and the requirements in the DSR guidelines by Hevner et al. (2004) were fulfilled.

The resulting framework's structure is based on the de-facto standard for maturity models, the Capability Maturity Model Integration and the similar Web Analytics Maturity Model. The components are linked with each other by a sequence flow modelled in Business Process Modelling Notation. The component-based framework allows flexibility, specifically for the different degrees of maturity in analytics that exist in enterprises.

In this paper, MCA is regarded as an extension of web analytics. Conducting the literature review and during the interview discussions and focus group it became clear that the high-level process is indeed applicable to web analytics when the key practices "appoint activities to channels", "evaluate data sources and methods for multichannel integration" and "evaluate actions and channels" are modified. The findings of this research contribute to several research areas such as web analytics, business analytics and business intelligence.

A limitation of the framework development process has to be seen in the fact that the framework has been tested only within one consulting organisation so far. Therefore, possible influencing factors such as company culture could have biased results. To minimise bias and composition error, predefined selection criteria and triangulation (i.e. a combination of multiple data collection methods) were used. For the literature review, a triangulation from different domains is assumed to reduce bias to a minimum. Furthermore, it has to be taken into account that a cross-sectional perspective has been chosen due to time restrictions. In future research, a longitudinal perspective might be appropriate for measuring e.g. the potential impact on effectiveness and efficiency possibly caused by the artefact in an organisation over time.

Half a year after its development, the MCAF is already in use at five organisations. Different consultants are using the framework. However, they all stem of one consultancy firm. To eliminate the above-mentioned company-cultural influences, it is proposed that the framework should be implemented and further validated using case studies in other companies either internally or by other consultancy firms.

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