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Evolution of Integrated Marketing Communication Research through Latent Dirichlet Allocation (LDA) Analysis

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Abstract
Integrated Marketing Communication (IMC) is an area that emerged as a shift in the way MarCom departments were functioning at the beginning of 90's. For the last 30 years, the concept evolved from being a tactical set of actions to a customer-focused strategy. Despite the great interest in the field and empirical studies that showed the great impact of implementing the concept in organisations, there are no studies that would have extracted the tendencies in the whole field of IMC development of the last decade. The purpose of this study is to investigate the general research trends with an emphasis on what topics were mostly in focus, which ones were diminished in order to understand the life cycle of the IMC theory and practice. This study analysed the distribution of topics in each of the research papers from the IMC area published in the last 10 years using Latent Dirichlet allocation (LDA), an unsupervised topic modelling approach that extracts topics from a collection of documents. The results were then compared against other content analysis studies from the previous decade. Education in the IMC area, measurement and performance were found to be the topics of the greatest interest and growth. This denotes the transition of the domain from building the unanimously accepted theoretical basis to the practical part of the concept like efficient implementation, measurement and monitoring of the performance. This study answers the question regarding IMC development stage placing it into maturity and identifies a slight decline in the overall efforts in the area. Also, the paper enables researchers with an example methodology on how to use a machine learning approach for efficient, unbiased and replicable content analysis. Further studies are needed to understand how the topics in the IMC area evolved over time and how they relate to topics in related fields.

Keywords: Integrated Marketing Communication (IMC), Latent Dirichlet Allocation (LDA), Topic Modelling.

JEL classification: M31.

1. Introduction

The development of the Integrated Marketing Communication (IMC) in the way it is now understood is largely due to the fact that towards the end of 1980s, the Department of Advertising, Direct Marketing and Public Relations of the Northwestern University changed its name into the Department of Integrated Communication (Schultz et al., 2014). This meant that the two practices (Advertising and PR) were merged together under the same concept. First definition of IMC was the result of an extended study (Schultz et al., 1993) realised by scholars from same university together with American Association of Advertising Agencies (AAAA). Out of this study, Schultz and his colleagues emphasise the fact that the communication message should be heard and understood correctly. This initial IMC abstraction through message consistency passed a series of development stages and evolved to include a myriad of new elements.

A series of authors made the attempt to create an overview of the researched subjects and used methodologies of IMC (Kliatchko, 2008; Schultz et al. 2014; Seric, 2015). In his article, Kliatchko (2008) reviewed the work on the domain from 1990 to 2006. Author extracts nine major categories of study and positions them chronologically (see Table 1).

Table 1. IMC Research Topics during 1990-2006

Researched Topic/ Period	*1990-1994*	*1995-1999*	*2000- 2006*
Concept Definition			
Practice of IMC			
IMC, PR and other controversies			
Global IMC			
IMC and managerial/organisational issues			
Measurement and performance auditing			
IMC and brand related issues			
Planning and interactivity of IMC used media			
IMC and internal marketing			

Source: Adaptation after table 1 from Kliatchko, J. (2008). Revisiting the IMC construct: A revised definition and four pillars. International Journal of Advertising, 27(1), 133-160, p.139.

In 2014, Schultz et al. come with an addition for the 2000-2009 period. The authors analyse a total of 44 scientific publications for the period in focus from 7 specialized journals. Results of the study are presented in Table 2.

Table 2. Number of articles according to the research field during 2003-2009

Research Field	***# Articles***	***Percentage***
IMC definition	*12*	*27%*
IMC perception	*9*	*20%*
Brand related aspects	*7*	*16%*
Measurement	*4*	*9%*
Interactiveness	*3*	*7%*
Media	*3*	*7%*
Performance	*2*	*5%*
Education	*2*	*5%*
Organisation	*1*	*2%*
Legal considerations	*1*	*2%*
Total:	*44*	*100%*

Source: Adaptation after table 23.5 from Schultz D.E., Ilchul K., Kyoungsoo K. (2014), "Integrated Marketing Communication Research Its Limited Past and Huge Potential", The Handbook of International Advertising Research

In the same study, the author imparts the 30 years of IMC research practice up to 2009 into three phases:

1) *Conceptualization* (1993-1997) characterized by works in the direction of concept identification and definition (Schultz et al., 1993; Caywood et al., 1991; Duncan and Everett, 1993; Nowak and Phelps, 1994; MacArthur and Griffin, 1997; Gould et al., 1999;)
2) *Diversification* (1998-2002) concentrated on the extension of the basic concepts of IMC. The researched topics include elements related to organizational and implementation aspects as well as cross-countries and global studies (Pickton and Hartley, 1998; APQC, 1998; Kitchen and Schultz, 1999; Eagle et al., 1999; Stuart and Kerr, 1999; Kallmeyer and Abratt, 2001; Reid et al., 2001).
3) *Consolidation* (2003-2009) characterized by the efforts of putting together and aligning all of the developed approaches, methodologies, best practices and performance measurement (Peltier et al., 2003; Reid, 2003, 2005; Madhavaram et al, 2005; Peltier et al., 2006; Eagle et al., 2007; Lee and Park, 2007)

The last content analysis of IMC publications (Seric, 2015) is focused on empirical studies. While the content is essential, it doesn't give an overview of the overall trend and current IMC phase.

This paper tries to address this gap by investigating the published articles on IMC, extracting individual subjects' trends. The purpose of this study is to answer: 1) what are the *general trends* in IMC research and how do they compare with the previous period 2) what *topics* were mostly in spotlight, and which one diminished. This will help understand the life cycle of the IMC theory and practice and identify the current development stage.

2. Methodology and data

All three studies (Kliatchko, 2008; Schultz et al., 2009; Seric, 2015) used a traditional systematization approach of the literature through content analysis. The manipulation and structuring of large collections of specialized papers on topics was done using coding sheets (Seric, 2015). However, human processing in the shape of coding practice may be substituted by computer processing for a series of reasons like reliability (King and Lowe, 2003), objectivity (Mo et al., 2015), time efficiency and possibility of applying it in the areas with little or no prior knowledge (Kevin et al., 2010). Also, one of the exciting things about text models is that they can distinguish effectively between competing meanings of the same term (DiMaggio et al., 2013).

2.1. Topic Modelling

Topic modelling has proven to be an effective tool for exploratory analysis of a large number of papers in a reliable, fast and reproducible way (Asmussen and Moller, 2019). From a technical perspective, topic modelling refers to a group of unsupervised machine learning algorithms that infer the latent structure behind a collection of documents. This means that there is no prior knowledge about topics included in an article and the method cannot leverage information about correct answers. The intuition behind topic models is that each article consists of a series of topics. A topic then refers to a collection of words or terms specific to it.

Some examples of modelling approaches are: Latent Semantic Analysis (LSA) (Deerwester et al., 1988), Probabilistic Latent Semantic Indexing (pLSI) (Hoffman, 1999), Latent Dirichlet Allocation (LDA) (Blei et al., 2003), Hierarchical Topic Modelling (hLDA) (Griffiths et al., 2003), Supervised Topic Modelling (sLDA) (Mcauliffe and Blei, 2007). For the current study the LDA modelling approach was selected, because it is by far the most popular, simple to understand and implement (Blei et al., 2003).

2.2. Notation and terminology

Before specifying the mathematical model associated with the topic approach, we define the following terms:

- A *word* w is the basic unit of text data. A word is an element of a vocabulary and is represented as a one-hot encoded vector of length of vocabulary. This means that the vector will have a value of 1 at word's position and 0 elsewhere. As an example, imagine having the vocabulary consisting of words {marketing, communication, efficiency, promotions}, the word "communication" is then codified as [0,1,0,0].
- A *document* d represents a sequence of N words noted by $d = (w_1, w_2, w_3, \ldots, w_N)$.
- A *corpus* is a collection of M documents noted by $D = \{d_1, d_2, d_3, \ldots, d_M\}$, where d_m is the m-th document in the collection.

2.3. Latent Dirichlet Allocation Method

The LDA model is a probabilistic generative method that extracts topics from a collection of papers. The LDA model assumes that a document contains a number of topics, so it is a probability distribution over topics. Each topic is defined as a probability distribution over words of a vocabulary. The method analyses the words in each paper and calculates the joint probability distribution between the observed elements (the words in the paper) and the unobserved ones (the hidden structure of the topics in the paper).

The *generative process* is described as follows (Blei, 2012):

- Primary *assumptions*:
  - There is a number of K topics in the documents collection
  - For each of the $k \in K$ topic, there is a distribution over words, $\beta_k \sim Dir(\eta)$
- *Document generation* process:
  - For each document $d = 1,..,M$, that is generated, is drawn a topic distribution that will be present in the document, $\theta_m \sim Dir(\alpha)$.
    - Based on this topic distribution, a topic is being randomly chosen $z_{m,n} \sim Multinomial(\theta_m)$
    - Based on the word distribution related to the chosen topic, a word is chosen randomly from the corresponding distribution over the vocabulary $w_{m,n} \sim Multinomial(\beta_k / k = z_{m,n})$
    - Previous two steps are iterated until the whole generation of the document is completed.

Thus, the main feature of LDA is the assumption that all documents in the collection have the same set of topics, but each document contains those topics in different proportions, from 0 to 1. In reality, we can only observe the words in a document, and we do not know the distributions that formed the basis of its generation (K, θ_m, β_k). Topics themselves, topics and words distributions are hidden variables. However, what is important to note is that the LDA process defines a joint probability distribution on both hidden variables (topics in a document) and observed variables (words in the document) as shown in figure 1. This joint distribution is used to deduce the hidden variables given the observed variables.

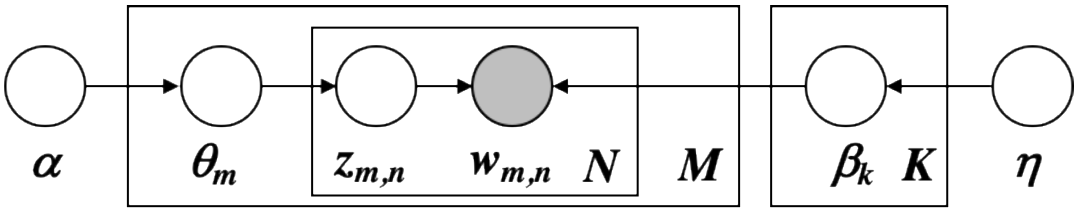

Figure 1. LDA Plate model notation

Source: Adaptation after figure 4 from Blei M. David. (2012), "Probabilistic Topic Models" Communications of the ACM, Vol. 55 Nr. 4, p. 81

Being a problem from the Bayesian paradigm, it is needed to compute the conditional distribution of the topic structure given the observed documents, or the so-called *posterior* distribution (Blei, 2012) by the help of the joint distribution of all the random variables (numerator) and evidence from data (denominator):

$$p(\beta, \theta, Z|w) = \frac{p(\beta,\theta,Z,w)}{p(w)} \quad \textit{(formula 1)}$$

As mentioned, in order to deduce the parameters of hidden variables, it is necessary to make use of the joint probability distribution of hidden and observed variables:

$$p(\beta, \theta, Z, w) = \prod_{k=1}^{K} p(\beta_k) \prod_{m=1}^{M} p(\theta_m) \prod_{n=1}^{N} p(Z_{m,n} \,|\theta_m)\, p(w_{m,n}|\beta_k = Z_{m,n}) \quad \textit{(formula 2)}$$

Same time, as it is computationally impossible to get the evidence (Blei, 2012), there is no way to directly calculate the posterior from *formula1*. Modern probabilistic modelling research developed efficient methods to approximate it. Particularly for LDA, there are 1) sampling-based algorithms like Gibbs Sampling (Griffits, 2004), 2) deterministic variational methods (Blei, 2003; Hoffman and Blei, 2010) and 3) hybrid ones (Teh et al., 2007) to be used in the inference. For the present study, the Hoffman and Blei approach will be used through *gensim* package in python programming language.

2.4. Data used

For the present study, a database of articles published between 2010 and 2019 was created. It comprises a number of 33 articles from 10 journals. The list of articles can be found in *Annex 1*.

2.5. Study Design

The framework used follows next steps: 1) Database creation 2) Documents cleaning 3) Text standardization 4) Document-Term Matrix creation 5) TF-IDF Matrix transformation 6) LDA and number of topics validation 7) Topic interpretation and overview.

Database creation: In the first step of creating the database, the articles are extracted in electronic format and their abstracts and titles are parsed. By parsing, it is identified the structure of the input text and brought up into a suitable form for further processing.

Documents cleaning: Next, the text was cleaned by removing punctuation and turning it into lowercase letters. This is necessary in order to be able to extract unique terms in a later step, because the computer does not consider equivalent the words "marketing" and "Marketing". In this step the commonly used words like “on, in, of, at etc.” are deleted as they are not carrying any informational value for our task.

Text standardization: In order to obtain uniqueness of terms, words must be brought to their original form (e.g. nominative for nouns and infinitive for verbs). This can be done by two methods: stemming and lemmatization. Stemming eliminates the suffixes that appear after the word inflection and bring words to the same stem (root) even if the root is not a valid word itself. On the other hand, the approach lemmatization is taking is to reduce the inflected words in a proper way by bringing them to their canonical or dictionary form. For these tasks are used programming packages with embedded language models.

Document-Term Matrix creation: After obtaining the unique roots, a common dictionary is created for all the documents. In our case, it was obtained a dictionary of 990 relevant terms. Using this dictionary, we compute the document-term matrix (DTM). DTM is a mathematical *MxN* sized (M documents and N words in the dictionary) matrix that describes the frequency of terms in a collection of documents. Values of the matrix are just absolute, relative or logarithmic frequencies of the term within each document, denoted with *tf* and calculated with:

$$tf_{w_n,d_m} = \begin{cases} \log\left(1 + f_{w_n,d_m}\right), \text{if } f_{w_n,d_m} > 0 \\ 0\,, \text{ else} \end{cases}, \qquad \textit{(formula 3)}$$

where f_{w_n,d_m} is the number of occurrences of the term w_n in document d_m, so that we have one *tf* value for each document-term pair.

In short, the *tf* frequency represents how popular a word is in a given document. In general, the higher the frequency, the higher probability the word is more representative for that specific document. The exception are the general terms that are used everywhere, in all documents. Some examples are language specific words (e.g. “and”, “or” etc). These would always get a high rank (high *tf* values) in all the documents without providing much useful insights about content.

TF-IDF Matrix transformation: As a result, by itself, the *tf* metric does not capture the most relevant words for a specific document. In order to downrank the common terms a second concept is needed: the inverse document frequency *idf*. The inverse frequency measures how popular or unique a term is across documents. It’s computed as the inverse fraction of the documents that contain the word:

$$idf_{w_n,D} = log\,\frac{M}{df_{w_n}} \qquad \textit{(formula 4)}$$

where D is the document corpus, M is the number of documents in D and df_{w_n} is the number of documents containing term w_n. The two components *tf* and *idf* are combined to create the *tf-idf* score:

$$tf.idf\ (w_n, d_m, D) = tf_{w_n,d_m} * idf_{w_n,D} \qquad \text{(formula 5)}$$

The *tf* value will rank higher the terms occurring often in a document, while *idf* will downrank the common terms. As a result, *tf-idf* will have higher values for terms that are very specific to a given document.

LDA and number of topics validation: In this step, *gensim* package for *python* is used to estimate LDA model parameters defined by the joint probability from *formula 2* using the *tf-idf* transformed DTM. The main question here is the number of topics, *K* that should be extracted from data. There are a couple of strategies on how to choose this number: 1) prior domain knowledge (Blei, 2003) 2) topic coherence measure (Newman et al., 2010; Mimno et al., 2011) and 3) manual evaluation by specialists.

Following the results of previous studies, Kliatchko (2008) and Schultz et al. (2014), it is chosen to run the model by setting *K* to {9,10}, as well as values close to them and then evaluate topic coherence. This strategy is a hybrid between previous knowledge in the field and usage of specialized measures. In essence, a topic coherence measure is an indicator of how consistent and consolidated topics are inside. Ideally, words are connected to each other through a word chain *(e.g. w1, w2, w1, w4)*, so that the word distributions in a topic make sense. In this work, the Mimno et al. (2011) *UMass* intrinsic coherence measure is used:

$$C_{UMass}\left(k, V^{(k)}\right) = \sum_{n=2}^{N} \sum_{l=1}^{n-1} log \frac{df\left(w_n^k, w_l^k\right)+1}{df\left(w_l^k\right)}, \qquad \text{(formula 6)}$$

where $V^{(k)}$ is the vocabulary given by LDA and related to *k*th topic, $df\left(w_l^k\right)$ is the number of documents in which w_l is present and $df\left(w_n^k, w_l^k\right)$ is the number of documents that have both terms w_l and w_n. An individual coherence is calculated for each topic and then an average is taken to represent the overall coherence for each of the *K* number of topics used. The overall coherence for each of the *K* values from 7 to 12 is shown in figure 2.

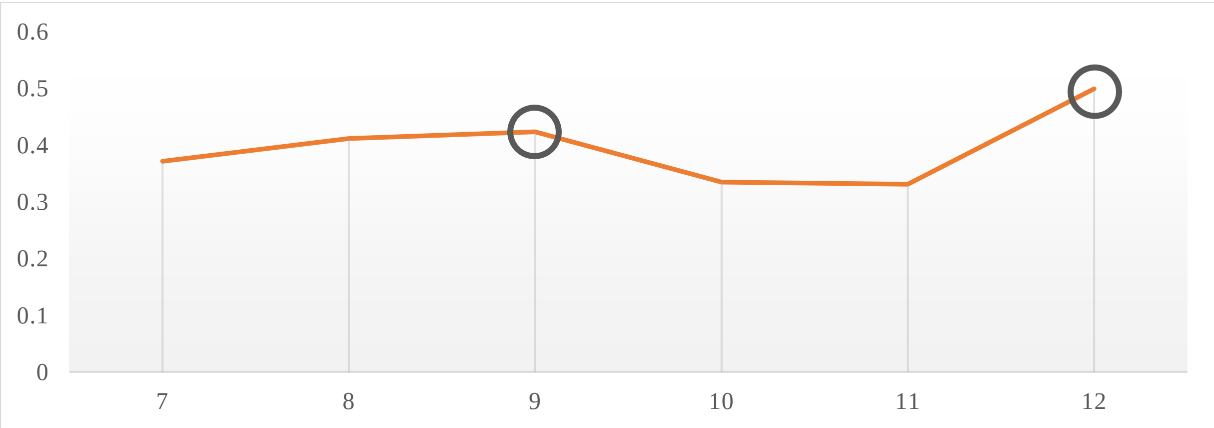

Figure 2. LDA output overall coherence by number of topics

Models with highest coherence (*K = 9, K = 12*) were manually checked in terms of topic assignment and topics' words distributions. It was concluded that the *K=9* model is more appropriate to be used because it doesn't show topic duplications as the *K=12* one. The output of the LDA (*K = 9*) model was interpreted and topics were annotated.

Thus, we extracted the following topics and their keywords:

1. *Perception*: advertising, agency, perception, public relations.
2. *Media*: switching, television, online, consumer, campaign.

3. *Education:* university, journal, manager, program.
4. *Implementation:* implementation, model, implication, development, practitioner.
5. *Performance:* performance, capability, effectiveness, financial, measure.
6. *Organizational:* officer, chief, phase, economy.
7. *Measure:* measure, panel, integration, valuator, diagnosis.
8. *Definition:* brand, review, framework, value, context.
9. *Interactivity:* medium, agency, interactivity, collaboration.

These topics are similar to those found in Schultz et al. (2014) research with exception of legal aspects field.

3. Findings

General trends. According to Schultz et al. (2014) study, during 1993-1997 an average of one article is published per year, between 1998-2002 the number increased to 3 research articles and between 2003-2009 to more than 6 articles. By contrast, during the period 2010-2019 it is observed an average of 3 articles published annually, which represents a decline in the research efforts of the IMC field. The journal with the largest coverage is the Journal of Marketing Communications with 10 publications.

Research topics results were summarised (table 3) and compared with previous Schultz et al. research.

Table 3. Number of papers according to topics and publication period

	2003-2009		*2010-2019*		
Research Topics	***Number of papers***	***% (A)***	***Number of papers***	***% (B)***	***Percentage Change (B/A)***
Definition	*12*	*27%*	*3*	*9%*	*0.30*
Education	*2*	*5%*	*7*	*21%*	*4.56*
Implementation	*7*	*16%*	*6*	*18%*	*1.12*
Interactiveness	*3*	*7%*	*3*	*9%*	*1.30*
Measurement	*4*	*9%*	*5*	*15%*	*1.63*
Media	*3*	*7%*	*3*	*9%*	*1.30*
Organization/Management	*1*	*2%*	*1*	*3%*	*1.30*
Perception	*9*	*20%*	*2*	*6%*	*0.30*
Performance	*2*	*5%*	*3*	*9%*	*1.95*
Legal	*1*	*2%*	*0*	*0*	-
Total papers:	*44*	*100%*	*33*	*~100%*	

Source: Adaptation after table 23.5 from Schultz D.E., Ilchul K., Kyoungsoo K. (2014), "Integrated Marketing Communication Research Its Limited Past and Huge Potential", The Handbook of International Advertising Research

By looking at the topic modelling results one can grasp a better understanding of the general trends in the IMC domain. Table 3 shows a time-based comparison of the article relative frequencies by research field. The first-time interval, 2003-3009, represents results from Schultz's study while the second one, 2010-2019 consists of more recent studies. The main research areas in recent years (2010-2019) are around IMC education (21%), IMC implementation (18%) and IMC result interpretation (15%). By comparing the values in the two columns, IMC education increased 3.5 times while IMC performance and result analysis increased 1.5 times.

On the other side, some areas are declining. ICM definition went from 27% to 9% while ICM perception dropped from 20% to 6%. One possible explanation is that IMC, as a concept, is maturing out of a "defining" phase towards a more "concept implementation and results" one. Kliatchko (2009) mentions that up until 2009, IMC efforts were put in building a strong foundation theory, to define the fundamentals of the concept.

Currently, a strong core foundation theory of IMC exists, and the focus is on the practical applications of the concept, on efficient implementation, monitoring, extraction of results and insights. IMC is clearly in its maturity phase with an emphasis on educating practitioners in using the concept.

Conclusions

Extracted IMC trends show an overall pattern towards diminishing efforts in the area. Same time, research topics that experienced a growth like efficient implementation, measurement of the results and monitoring of the performance denote the fact that at this point, IMC is back to the tactical questions of integration. Although IMC is focusing now on the educational aspect that will ensure a significant concept usage, and the area shows signs of maturity, its decline is a question of agility of integrating new technologies. In order to make IMC paradigm feasible, it should be aligned to the AI trend that is taking over all areas.

Having this in mind, in this paper, a novel approach of extracting trends in a specific research domain was presented. The used study framework was based upon the application of the Latent Dirichlet Allocation topic modelling approach. Topic modelling and text mining is an exciting machine learning field which advantages can be leveraged in order to analyse research papers in an efficient, reliable and low-cost manner. The obtained results show high consistency with the previously human conducted content analysis.

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Annex 1: *List of articles used in the study*

Title	***Year***	***Journal***	***First Author***
Integrated Marketing Communications (IMC): Why Does It Fail?	2015	JAR	Mart Ots
Is the Multi-Platform Whole More Powerful Than Its Separate Parts?, Measuring the Sales Effects of Cross-Media Advertising	2013	JAR	Jennifer Taylor
From Silos to Synergy A Fifty-year Review of Cross-media Research Shows Synergy Has Yet to Achieve its Full Potential	2011	JAR	Henry Assael
Do adhocracy and market cultures facilitate firm-wide integrated marketing communication (IMC)?	2015	IJA	Lucia Porcu
Discovering prominent themes in integrated marketing communication research from 1991 to 2012: a co-word analytic approach	2014	IJA	Francisco Muñoz-Leiva
Integrated Marketing Communication Capability and Brand Performance	2014	JA	Sandra Luxton
Twenty years of IMC A study of CEO and CMO perspectives in the Asia-Pacific region	2015	IJA	Kliatchko J.
IMC – an integrative review	2014	IJA	Wondwesen Tafesse
IMC in an emerging economy: the Chinese perspective	2016	IJA	Schultz D.E.
IMC in digitally-empowering contexts: the emerging role of negotiated brands	2018	IJA	Agostino Vollero
Integrated marketing communications: How can we measure its effectiveness?	2010	JMC	T. Reinold
Integrated marketing communications, brand equity, and business performance in micro-finance institutions: An emerging market perspective	2018	JMC	Peter Anabila
Improving integrated marketing communications practices: A comparison of objectives and results	2014	JMC	C.H. Patti

Examining the link between integrated communication management and communication effectiveness in medium-sized enterprises	2011	JMC	Sabine A. Einwiller
A study of the structural integration of the marketing and PR functions in the C-suite	2014	JMC	Pravin Nath
Strategic antecedents and organisational consequences of IMC in different economy types	2019	JMC	Vera Butkouskaya
Content analysis of the empirical research on IMC from 2000 to 2015	2016	JMC	Maja Šerić
Strategic IMC: From abstract concept to marketing management tool	2012	JMC	Gayle Kerr
Partner or supplier: An examination of client/agency relationships in an IMC context	2017	JMC	Kathleen Mortimer
The diversity of advertising formats and the need to revisit the empirical bases of IMC	2017	JMC	Kitchen P.J.
'IMC is dead. Long live IMC': Academics' versus practitioners' views	2011	JMM	Sally Laurie
How to achieve true integration: the impact of integrated marketing communication on the client/agency relationship	2018	JMM	Sally Laurie
Integrating social media within an integrated marketing communication decision-making framework	2016	JMM	Michael J. Valos
Using Means-End Analysis to Test Integrated Marketing Communications Effects	2010	JPM	John M. McGrath
Drivers of Globally Integrated Marketing Communications: A Review of Literature and Research Propositions	2011	JPM	Mabel Zvobgo
An IMC Process Framework for a Communications-Based Services Marketing Model	2010	JPM	Jeffrey W. Von Freymann
Same But Different—Perceptions of Integrated Marketing Communication Among Marketing Communication Partners in Australia	2010	JPM	Gayle Kerr
The implementation of integrated marketing communication (IMC): evidence from professional football clubs in England	2019	JSM	Argyro Elisavet
Developing an integrative model of internal and external marketing	2013	JSM	Ahmed Shahriar Ferdous
The Next Integration: IMC and the Field of Communication	2011	RM	S. Alyssa Groom
The impact of IMC consistency and interactivity on city reputation and consumer brand engagement: the moderating effects of gender	2018	CIIT	Maja Šerić
Unlocking the Power of Integrated Marketing Communications: How Integrated Is Your IMC Program?	2016	JA	Keller K.L.
Integrated Marketing Communications and Their Effects on Customer Switching Intention	2016	JRM	Paramaporn Thaichon

Note*: CIIT = Current Issues in Tourism, IJA = International Journal of Advertising, JA = Journal of Advertising, JAR = Journal of Advertising Research, JMC = Journal of Marketing Communications, JMM = Journal of Marketing Management, JPM = Journal of Promotion Management, JRM = Journal of Relationship Marketing, JSM = Journal of Strategic Marketing, RC = Review of Communication*