Padmaka Mirihagalla – Gyula Vastag

Maturity models – Taking stock and moving forward

PADMAKA MIRIHAGALLA
PhD Student
Széchenyi István University,
Hungary
Email: mirihagalla.padmaka@sze.hu

GYULA VASTAG
Research Professor
Corvinus University, National University of Public Service,
Hungary
Email: vastag.gyula@uni-nke.hu

Maturity models (MMs) are based on the premise that improved maturity in organisational capabilities leads to improvements in the desired outcome measures. This promising potential explains the growing popularity of MMs and the large number of publications on the subject in various academic and professional journals. The present study is based on an analysis of 339 MM papers published in 193 journals between 1973 and 2017. After giving a brief overview of the theoretical underpinnings of MMs, the authors focus on answering the question of 'where to publish to achieve maximum impact' from the perspective of potential authors. The impact of a publication, measured by the number of citations collected over its lifetime, is influenced by the quality of the journal (measured by the journal's article influence score by Clarivate Analytics, Scimago Journal Ranking by Scimago, and Scimago Q category) and the length of public availability of the publication. Results from a variety of partitioning models (decision tree, bootstrap forest, and boosted tree) show that publishing in high-quality, recognised journals tends to result in more citations. In other words, in a network of journals, not all citations are equal as citations in selective, highly ranked journals are more equal than others. It is also important to emphasise that Scimago's Q classification has no bearing on a paper's post-publication success; Q classification is a noisy and poor measure of a journal's quality that is not used globally.

KEYWORDS: maturity models, publication impact, journal quality

In the literature, 'maturity' is generally referred to as a condition or phase that can be defined, measured, managed, and controlled (*Mettler* [2010]). A maturity model (MM) consists of a hierarchy of anticipated maturity levels and represents the typical path of evolution of a given capability (*Becker–Knackstedt–Pöppelbuß* [2009]).

The objective of an MM is to provide direction and clarity through this evolutionary path which eventually leads to the definition of improvement activities (*Mettler* [2010]). Although MMs come in different forms and types, the principal concept is that they describe a few sequential phases, the typical behaviour exhibited by a firm, and the level of sophistication of processes (*Fraser–Moultrie–Gregory* [2002]).

The concept of MMs emerged in the 1970s through *Gibson–Nolan* [1974] and *Crosby* [1979], with the original capability maturity model (CMM) of *Paulk et al*. [1993] being the turning point of the attention towards MMs. Although it had been almost four decades since the introduction of the original CMM, the application of MMs in the academic literature has sharply increased in terms of number and diversity (*Santos-Neto–Costa* [2019]). Furthermore, MMs have been questioned for their theoretical rigor throughout this period (*Poeppelbuss–Simons* [2011], *Monteiro–Maciel* [2020]).

Systematic reviews providing a thematic analysis (e.g., *Poeppelbuss–Simons* [2011], *Reis–Mathias–de Oliveira* [2016], *Wendler* [2012], *Tarhan–Turetken–Reijers* [2016], *Vallerand–Lapalme–Moïse* [2015], *Santos-Neto–Costa* [2019], *Monteiro–Maciel* [2020]) and evaluation of MMs, along with their design principles (e.g., *de Bruin et al.* [2005], *Becker–Knackstedt–Pöppelbuß* [2009], *Pöppelbuß–Röglinger* [2011], *ISO* [2015]) have been comprehensively conducted by numerous studies. Most systematic reviews involve a detailed descriptive statistical analysis of the themes of MMs and where they have been published (e.g., *Santos-Neto–Costa* [2019], *Monteiro–Maciel* [2020]). However, no study has analysed the qualitative parameters of journals in which these continuously growing number of MMs have been published. Given the increasing number of published studies on MMs, the broadening diversity of the capability domains of MMs, and the great criticism of the methodological rigor of MMs, it is now interesting to explore the distribution of MMs across different journal ranks and to check whether publishing in higher-ranked journals means higher visibility or impact for MMs.

The current study examines 339 articles on MMs published between 1973 and 2017 and measures their impact in terms of the number of citations they have received over their lifetime. The quality of the journals that published these MM articles is also measured by their article influence score (AIS), Scimago Journal Ranking (SJR), and Scimago quartile (Q). Through various analyses of these two variable sets, this study explores the distribution of MM articles in journals and attempts to answer the question of 'where to publish MM articles to achieve the maximum impact' from the point of view of potential authors.

1. Maturity models: an overview

The information systems (IS) literature first introduced the concept of MMs in the 1970s as a method to control performance. The computational resource MM of *Gibson–Nolan* [1974] and the five-level quality management process grid (*Crosby* [1979]) are often cited as pioneering works of MMs (*Humphrey* [1988]). At the request of the US Department of Defense, Carnegie Mellon University (*Paulk et al.* [1993]) developed the CMM, which was based on the principles of *Crosby* [1979]. Later, the CMM further evolved into CMM Integration (CMMI) in 2001 with the integration of existing CMMs (*Veldman–Klingenberg* [2009], *Liou* [2011]). CMMI defines the critical elements of a mature process and describes how an enterprise can move from lower maturity levels to higher ones (*Day–Lutteroth* [2011]). Many systematic reviews claim that CMMI is the turning point of the development and publication of MMs and has become an influential methodological base. The introduction of MMs from diverse capability domains has since become apparent in existing research. Table 1 shows a list of such diverse domains where MMs have been introduced on the basis of the information technology-related MMs of the 1990s.

MMs are structured models. *Pullen* ([2007] p. 9) defined an MM as 'a structured collection of elements that describe the characteristics of effective processes at different stages of development.' Further, MMs clarify the demarcation between phases and procedures within the transformation journey of maturation (*Pullen* [2007]). *Klimko* ([2001] p. 271) stated that the concept of 'maturing' describes 'the development of an entity over time. This entity can be anything of interest: a human being, an organizational function, etc.' Most MMs are made up of several elements. Domain components represent the level 1 breakdown of an umbrella-level capability. For example, in the MM of digital transformation uses (*Gökalp–Martinez* [2021]), strategic governance, information technology, digital process transformation, and workforce management are the domain components. In the MM of Industry 4.0 uses by *Wagire et al.* [2020], people and culture, Industry 4.0 awareness, organisational strategy, value chain and processes, smart manufacturing technology, product- and service-oriented technology, and Industry 4.0 base technology are the domain components. In MMs, the domain components are further split into indicators. Indicators are attributes subjected to measurement. For example, *Wagire et al.* [2020], within the domain component 'people and culture', used 'leadership support towards digital transformation activities' as one of the indicators. MMs use different methods to assign numerical values to indicators for measuring maturity. The most common methods are the use of a Likert scale (e.g., *Santos Bento–Tontini* [2018] in their lean MM) or stage definitions adapted from CMMI (e.g., *Gökalp–Martinez* [2021]).

Table 1

Examples of studies introducing MMs in diverse capability domains

Capability domain	Study
Blockchain	*Wang–Chen–Xu* [2016], *Ronaghi* [2020]
Business process management	*Tarhan–Turetken–Reijers* [2016], *Van Looy–de Backer–Poels* [2011]
Digital transformation	*Gollhardt et al.* [2020], *Gökalp–Martinez* [2021]
Education	*Zhou* [2012], *Egberongbe–Sen–Willett* [2017], *Al-Ammary–Mohammed–Omran* [2016], *Garbin–ten Caten–de Jesus Pacheco* [2021]
E-governance, e-government	*Misra–Dhingra* [2002], *Anza–Sensuse–Ramadhan* [2017], *Valdés et al.* [2011], *Concha et al.* [2012], *Chohan et al.* [2020]
Industry 4.0	*Schumacher–Erol–Sihn* [2016], *Ganzarain–Errasti* [2016], *Wagire et al.* [2020]
Knowledge management	*Serenko–Bontis–Hull* [2016], *Hsieh–Lin–Lin* [2009]
Lean manufacturing	*Maasouman–Demirli* [2015], *Nightingale–Mize* [2002]
Marketing	*Hirschheim–Schwarz–Todd* [2006], *Seebacher* [2021]
Medical and healthcare	*McCarthy et al.* [2014], *Blondiau–Mettler–Winter* [2016], *Sullivan et al.* [2016]
Product development/new product development	*Fraser–Moultrie–Gregory* [2002], *Vezzetti–Alemanni–Morelli* [2016]
Project management	*Kwak–Ibbs* [2002], *Grant–Pennypacker* [2006], *Pasian–Sankaran–Boydell* [2012]
Quality management	*Xiaofen* [2013], *Ramadan–Arafeh* [2016]
Risk management	*Salawu–Abdullah* [2015], *Zhao–Hwang–Low* [2014]
Safety culture	*Goncalves–Andrade–Marinho* [2010], *Phusavat–Vongvitayapirom–Hidayanto* [2015]
Social media	*Duane–O'Reilly* [2012], *Lehmkuhl–Baumol–Jung* [2013]
Supply chain management	*Lockamy–McCormack* [2004], *Souza–Guerreiro–Oliveira* [2015]
Sustainability	*Prashar* [2017], *Ferreira–Jabbour–Jabbour* [2017]

Largely because of their structural straightforwardness and ability to provide insights purely on theoretical grounds, it is intuitively appealing to develop and cognitively confirm the benefits of MMs (*Tarhan–Turetken–Reijers* [2016]). With the growing popularity of these models, the emergence of studies involving systematic literature reviews on MMs has become noticeable (e.g., *Lasrado–Vatrapu–Andersen* [2015], *Monteiro–Maciel* [2020], *Wendler* [2012], *Santos-Neto–Costa* [2019], *Reis–Mathias–de Oliveira* [2016]). There are also studies that examine the weaknesses of MMs (e.g., *Buckle* [2018], *Kohlegger–Maier–Thalmann* [2009], *Mullaly* [2014]) and studies proposing MM development guidelines, principles, and processes (e.g., *de Bruin et al.* [2005], *Maier–Moultrie–Clarkson* [2009], *Mettler* [2010], *Pöppelbuß–Röglinger* [2011], *Van Looy et al.* [2013], *ISO* [2015], *Becker–Knackstedt–Pöppelbuß* [2009]). However, studies that deeply review MMs' rigor, validity, and usefulness in relation to the real-life evidence of utility are scarce (*Tarhan–Turetken–Reijers* [2016]).

Santos-Neto–Costa [2019], after reviewing more than 400 MMs, revealed that only 3% of MMs have been empirically validated. If MMs are growing in volume and diversity and if they have been criticised for their rigor and, most importantly, for their validity, then it would be interesting to understand the demographics of papers and the journals that published them. Most systematic reviews analyse the domain of MMs and the journals where they have been issued. However, understanding the demographics and academic performance of published media has not received much attention. *Monteiro–Maciel* [2020] claimed that most MMs have been published in conference proceedings possibly because of the less methodological and empirical rigor they demand. *Gökalp–Martinez* [2021] revealed that 55% of the MMs of digital transformation have been published in conference proceedings. However, there remain hundreds of papers on MMs that have been published in academic journals. The impact of these papers and the journals that published them on their post-publication life remains an uncharted territory.

2. Data and methods

This study examines the various parameters of 339 MM articles published between 1973 and 2017 to answer the research questions (RQ) below. RQs 1–3 describe the journals in which MM articles were published using graphical charts. RQ 4 focuses on the impact of MM papers using various partitioning models (decision trees and bootstrap forest).

*RQ*1: *How has the number of MM articles published across SJR quartiles changed over the years?*

*RQ*2: *How are published MM articles distributed across different journal categories?*

*RQ*3: *What is the distribution of MM articles across journals and how are these journals ranked?*

*RQ*4: *Does publishing in higher-ranked journals result in more citations?*

2.1. Selection of papers on MMs

The initial search was conducted on four digital databases (Web of Science, Scopus, SpringerLink, and ScienceDirect) by using the following keywords: maturity model, maturity approach, phase-based maturity, and staged maturity. Five stages of filtering were performed sequentially to obtain the sample used in this study. The sequence of exclusion criteria (and subsequent deletion from the sample) were *1*. articles from non-business domains; *2*. articles published in 2018 or later; *3*. articles that were not from journals (e.g., conference papers and books); *4*. articles not primarily about MMs (based on the title and abstract); and *5*. articles from journals that did not have an SJR during the journals' lifetimes. The rationale for the removal of conference papers and books was the absence of the two most critical quality parameters in this study: SJR and AIS (see description in the next subsection). A similar rationale applied to journals that were not listed in Scimago. Since the number of citations was used as the dependent variable of the analysis, articles published in 2018 and onwards were excluded, thus resulting in four years for the articles published in 2017 to gather citations. After the final filter, the list was further scrutinised for any duplicate MMs cited by authors in multiple articles; a few such articles were removed.

The final list consisted of 339 papers published in 193 journals representing 13 fields (IT dominated with 116 papers, followed by engineering with 49 papers). Most papers (222 of the 339) were published in journals in the upper half (Quartile 1 [Q1] and Quartile 2 [Q2]) of the Scimago quality classification. On average, a paper was cited 92 times, and the maximum number of citations was 1,880 in Google Scholar.

2.2. Variables and data sources

In terms of the variables to judge journal quality, the SJR, Scimago (Q), and AIS by Clarivate Analytics were used. The SJR and AIS are network centrality measures (similar to Google's Page Rank) that use the number of citations throughout the network of journals in the respective databases to determine the importance of each journal which is reflected in the expected potential influence of a paper published in the journal. The SJR and AIS measure the influence of a given journal (factoring in the number of papers published by the journal). There are three major differences between the SJR and AIS.

1. The SJR uses Elsevier's Scopus database with approximately 36,000 journals, whereas AIS relies on Clarivate Analytics' highly selective Journal Citation Reports with about 13,000 journals.

2. The SJR uses a citation window of three years, and the AIS is based on a five-year window of citations.

3. Self-citations – up to a certain limit – are allowed in SJR, whereas there are no self-citations in AIS.

The most popular Q classification is performed by Elsevier (that is also a publishing company) using the SJR values of journals in a category, which are also determined by the publisher. Consequently, a journal can have several Q categories at any given time. It must be noted that in this context, Elsevier is 'wearing two hats', that is, the company acts as a publisher of journals and an indexer of the same set of journals. By contrast, Clarivate does not publish journals.

Table 2 lists the sources and specific criteria used to collect the data for each of the 339 articles.

Table 2

Key variables, data sources, and data collection criteria

Variable	Source	Criterium
SJR	https://www.scimagojr.com	SJR (publication year): publication year as per the reference or, if it was not available, the closest to the publication year* SJR (latest): 2020
Q	https://www.scimagojr.com	Q (publication year): publication year as per the reference or, if it was not available, the closest to the publication year* Q (latest) quartile of 2020
AIS	http://www.eigenfactor.org https://jcr.clarivate.com/	AIS of the publication year or, if it was not available, the closest to the publication year**
Number of citations	https://scholar.google.com	Number of citations received by the article as of 31st October 2021

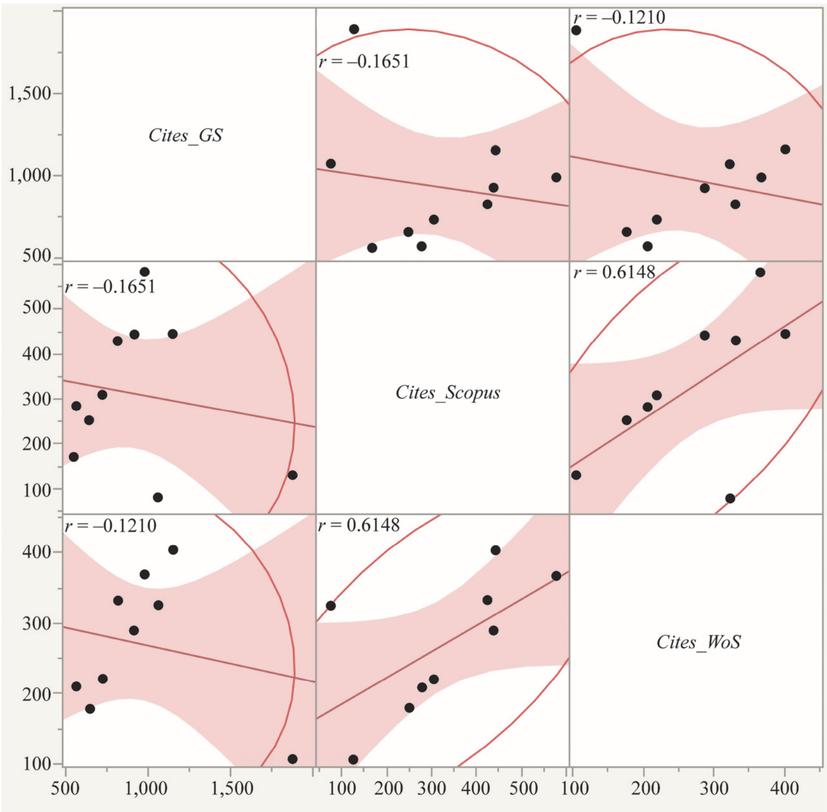
* SJR is available only from 1999 and in some cases, the journal had not been qualified within Scimago.

** AIS is available only from 1997 and in some cases, the journal had not been qualified within the AIS system.

Note. *Q* refers to journal quartile.

Google Scholar is a 'robot' that scours the Internet and collects every document (without checking its 'pedigree') that cites a paper. Scopus and Web of Science rely on human judgement to determine the inclusion list of journals in the searched databases. Given how these searches are set up, Google Scholar citations far outnumber those of the other two, with Scopus being a distant second. Collecting citations from all three sources was beyond our capacity; however, as an illustration, we examined the top 10 papers with the most citations in Google Scholar and compared them with those in Scopus and Web of Science (see Figures 1 and 2). In each scatterplot, a 95% bivariate normal density ellipse, regression line, and Pearson correlation coefficient are shown. Assuming that each pair of variables has a bivariate normal distribution, the ellipses enclose approximately 95% of the points. The narrowness of the ellipse reflects the degree of correlation between variables. If the ellipse is fairly round and not diagonally oriented, then the variables are uncorrelated. If the ellipse is narrow and diagonally oriented, then the variables are correlated.

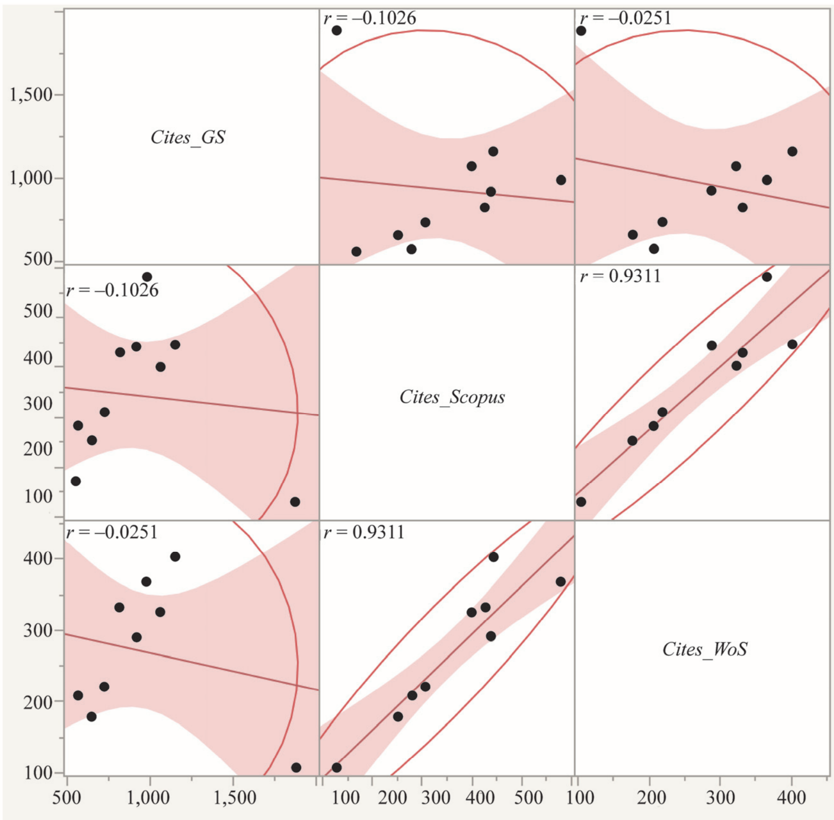
Figure 1. Scatterplot matrix of citations in Google Scholar (Cites_GS), Scopus (Cites_Scopus), and Web of Science (Cites_WoS)



Somewhat surprisingly, we could not find Web of Science citation data for a 2003 paper in the *International Journal of Project Management*; hence, only nine points are shown in the scatter plots. In addition, a 2009 paper in the Springer *Journal of Business & Information Systems Engineering* had 78 citations in Scopus – it seemed to be an outlier – and 401 citations in Springer Link. In Figure 1, this outlier lies in the right middle panel of Cites_WoS and Cites_Scopus; this is a point close to the horizontal line. In Figure 2, after replacing the Scopus citation with the Springer number, this point moves up very close to the regression line.

The Web of Science and Scopus citation numbers show a medium positive correlation, which is further strengthened by the mentioned correction. Meanwhile, the Google Scholar and Scopus citation numbers show a weak correlation, and, surprisingly, the Google Scholar citations are negatively correlated with those of the Web of Science.

Figure 2. Scatterplot matrix of citations in Google Scholar (Cites_GS), Scopus (Cites_Scopus), and Web of Science (Cites_WoS) – corrected data



Note. See the text for explanation.

2.3. Methods

2.3.1. Data preparation

Additional parameters were added to the data worksheet to generate meaningful descriptive and inferential insights.

> *1. Journal category*: Most journals are tagged with multiple categories within Scimago, and the number of categories can be diverse and uneven. Hence, we studied the scope description of each journal (available on the journal website) and assigned it with a single category (e.g., IT, sustainability, and project management).
>
> *2. Net SJR*: This is the difference between each journal's SJR in its publication year and its SJR in 2020. The value shows whether the SJR value has changed since article publication. The average net SJR was used in the analysis when a single journal published multiple MM articles in different years.
>
> *3. Delta Q*: This is the difference between the Q categories in the publication year and in 2020. This value shows whether the journal has moved between quartiles since the publication of the MM article.
>
> *4. Q*1 *and Q*2 *deciles*: Given the number of the business journals listed in Scimago, Q classification could be too broad to make a correct judgement. Hence, the top two quartiles (Q1 and Q2) of all business journals within Scimago were further split into deciles within each Q. For example, if a journal was given the value Q1-1, that journal would be in the first 10% of ranked journals within the Q1 journals; if a journal was given the value Q2-2, that journal would be in the second 10% of ranked journals within the Q2 journals. This classification helps to break the list of journals down into ranked volumes that can be more meaningful than taking the Q classification because of the sheer size of business journals listed within Scimago.

2.3.2. Data analysis techniques

Descriptive statistical charts are used for the prepared data (see 2.3.1. Data preparation) to gain insights into the subject of *RQs* 1–3. To answer *RQ*4, partitioning models (decision trees, bootstrap forests, and boosted trees) are employed.

3. Analysis

This section is organised on the basis of the *RQ*s.

*RQ*1: *How has the number of MM articles published across SJR quartiles changed over the years?*

Figure 3 shows the distribution of the volume of MM articles across different years from 1973 to 2017, with each bar split into the composition of quartiles to which the respective journals belong. The gradual growth in volume began in 2005, with 2016 marking the year with the highest number of MM articles published. However, the journals of Q1 started increasing in volume in 2008, and since 2014 it has shown a possible declining trend; in Q2 and Q3, their volume has increased at a higher rate, thus creating an overall growth in volume.

Figure 3. Number of MM articles published in each year within each quartile

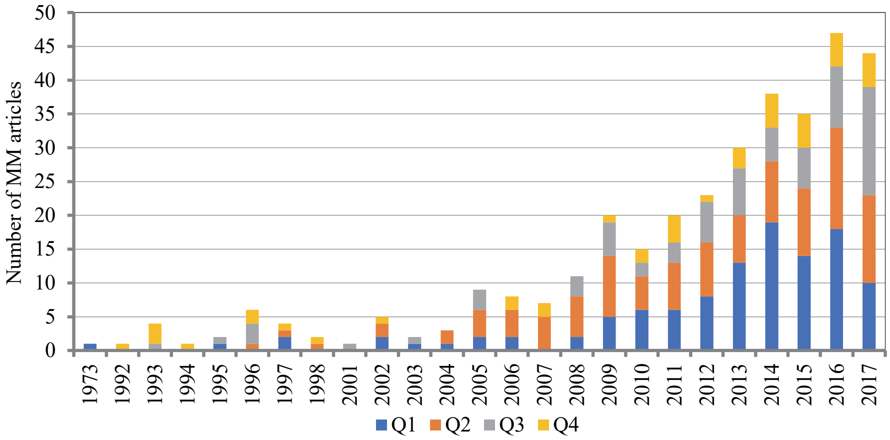
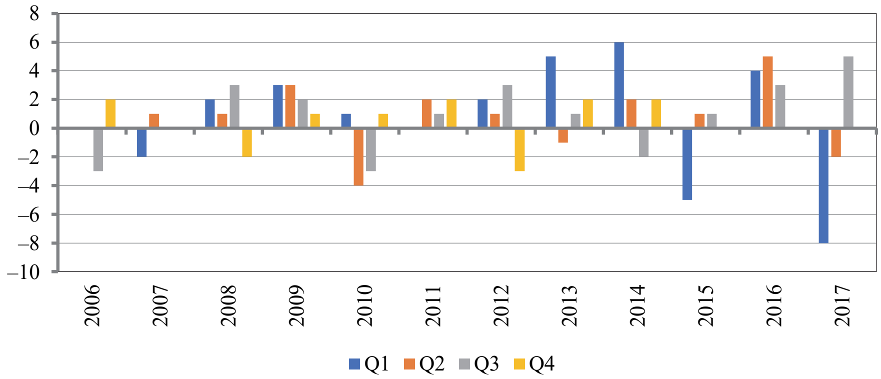


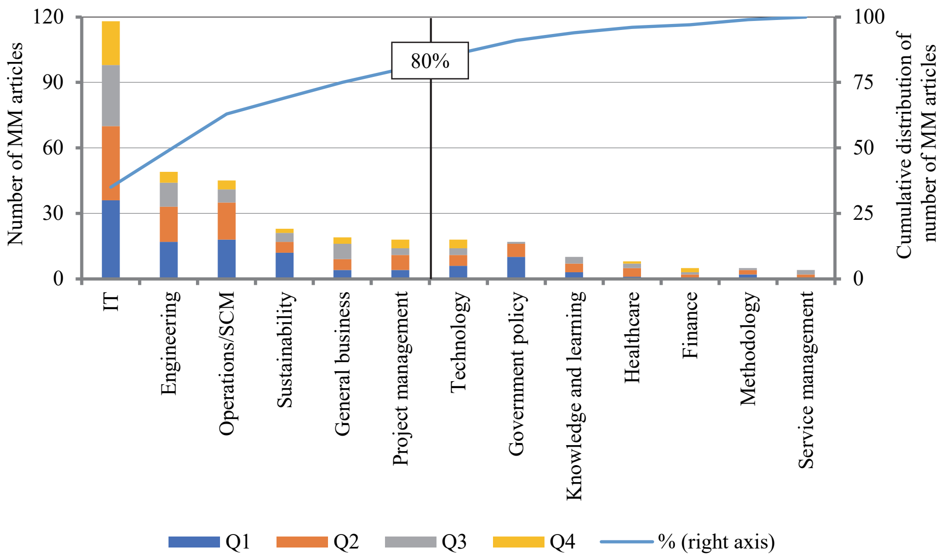
Figure 4. Delta number of MM articles from preceding year



RQ2: How are published MM articles distributed across different journal categories?

Figure 5 shows the distribution of the volume of MM articles across journal categories (for the description, see 2.3.1. Data preparation), with the volumes within each quartile stacked. IT journals are dominantly publishing MM articles along with engineering, operations/supply chain management (SCM), sustainability, general business, and project management journals, which together account for 80% (271 out of 339). It is also clear that journals within all four quartiles in the top journal categories have published MMs.

Figure 5. Number of MM articles distributed within journal categories and quartiles, 1973–2017

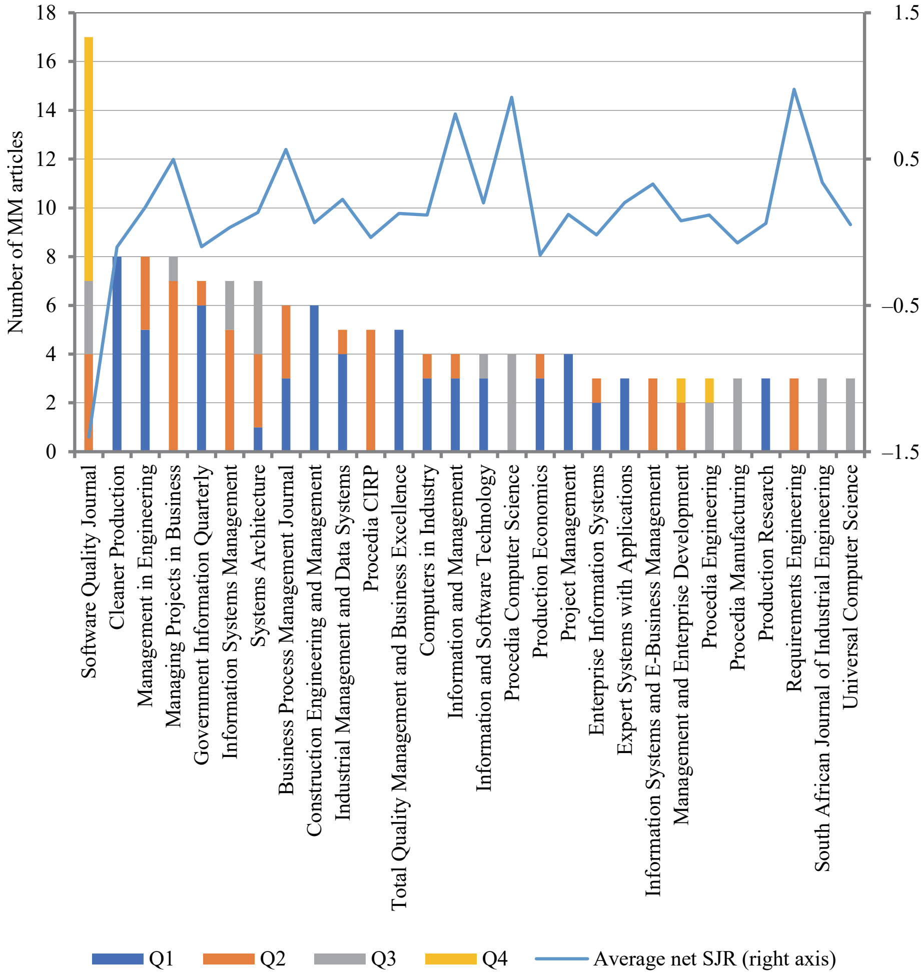


Note. SCM: supply chain management.

RQ3: What is the distribution of MM articles across journals and how are these journals ranked?

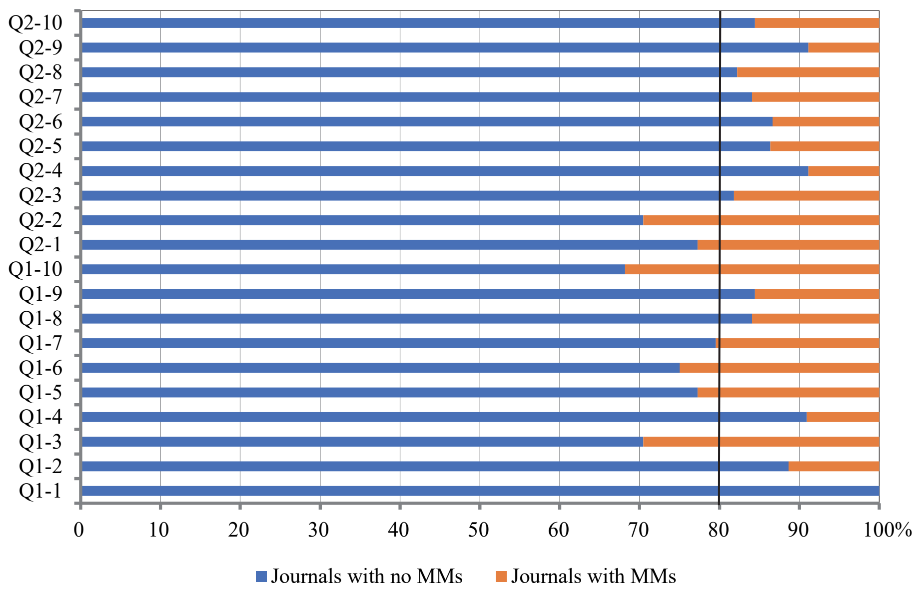
Figure 6 shows the number of MM articles distributed across journals which published three or more MM articles from 1973 to 2017. Each bar represents a journal and the number of published MMs within each quartile. The average net SJR (explained in 2.3.1. Data preparation) is the average of the net SJR values of the publication years of each MM article (and denotes the average movement of the journal within its Scimago ranking). The *Software Quality Journal* leads the publication of MM articles relative to other journals. However, it is noticeable that this journal did so whilst being a Q4 journal, and it has a high negative average net SJR, indicating that during the study period, the journal had mostly lost its ranking. Almost all the other journals show positive average net SJR values, demonstrating a growing ranking during the period in which they published MM articles.

Figure 6. Top journals that published three or more MM articles and their movement in SJR, 1973–2017



Providing further insights into *RQ*3, Figure 7 shows the percentages of journals that published MM articles within each decile in the Q1 and Q2 ranks (explained in 2.3.1. Data preparation). In each of the deciles within Q1 and Q2, the majority of the journals (the lowest was slightly below 70% in Q1-10, and the highest was 100% in Q1-1) did not publish any MM articles. On average, 82% of the journals did not publish any MM articles, which means that only 18% of the top 50% journals (Q1 and Q2) published MM articles (standard deviation = 8%).

Figure 7. Proportion of journals within each decile in Q1 and Q2, which have published MM articles, 1973–2017



RQ4: Does publishing in higher-ranked journals result in more citations?

To understand whether 'it is better to publish MM articles within specific deciles within the zone of Q1 and Q2 from a citation point of view', Figures 8 and 9 show two panels. Figure 8 indicates the volumes of MM articles published within each decile for both Q1 and Q2 journals and the average number of citations that each MM article has attracted since its publication. The dotted plot in Figure 9 illustrates the correlation between the two variables. Three specific zones attract more MM articles (Q1-3; Q1-10 and Q2-1; and Q2-8). The average number of citations per MM article follows the trend of the volume of MM articles within the decile. This was statistically confirmed in the dot plot chart with a correlation of 0.734.

Figure 8. Number of MM articles published within a decile for Q1 and Q2 journals and average number of citations per MM article within each decile, 1973–2017

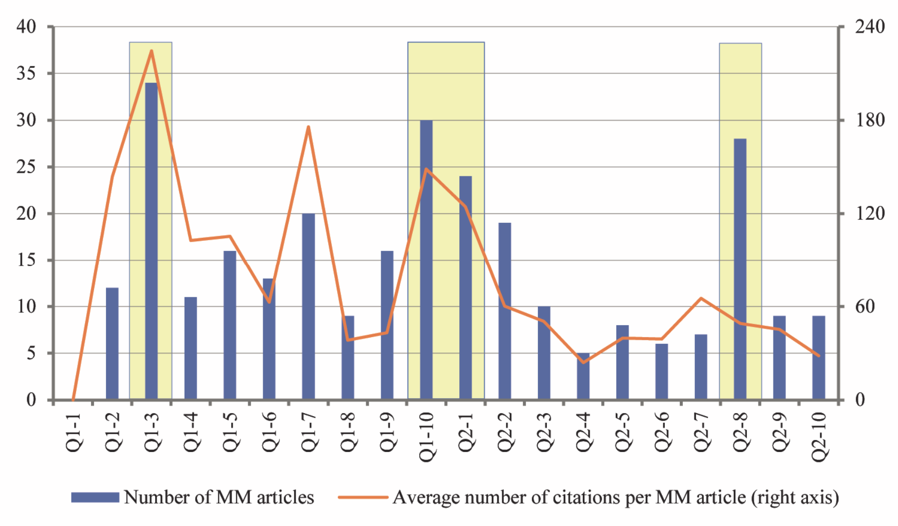


Figure 9. Correlation between number of MM articles published within deciles for Q1 and Q2 journals and average number of citations per MM article within deciles, 1973–2017

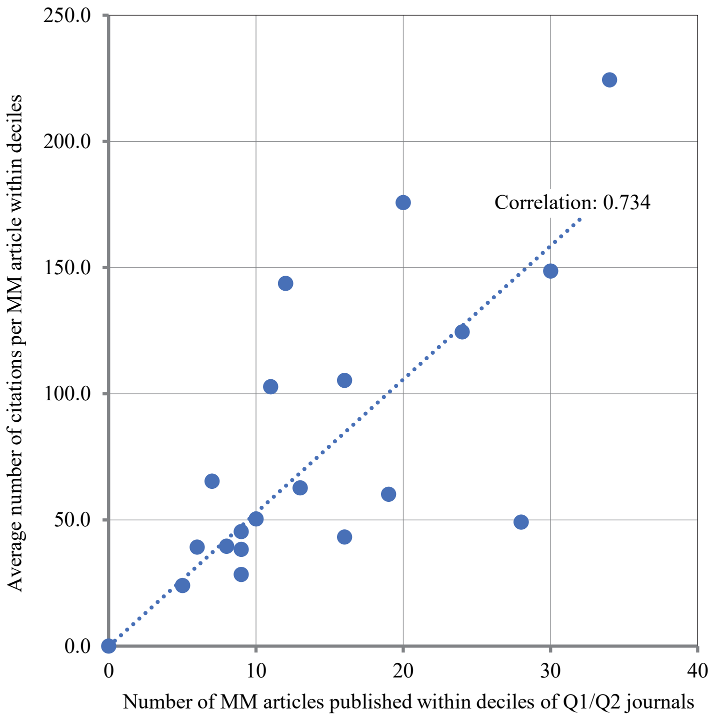


Figure 10 presents a partitioning (or decision tree) model. The regression tree[1] shows the number of citations as a response variable and various journal quality measures (AIS, SJR numbers, and the Q classification at the time of publication) and the year of publication showing the elapsed time as predictors. The response variable is continuous (hence, it is a regression tree) and so are some of the predictors. The Q classification is categorical/ordinal. Missing values (only 210 out of 339 papers were published in journals with AIS values at the time of publication) were handled as 'informative missing values'. With this option, observations for continuous variables with missing values are first considered to be at the low end of the split for each possible split evaluated. Then, they are assumed to be at the high end of the split for each possible split. A split with the best LogWorth[2] was selected.

Once the missing observations are put into one of the sides, they remain there for further splits on that factor. An alternative to 'informative missing' is to use imputation: observations with missing values are randomly assigned to one side of the split. With this dataset, both approaches were tried, but as expected, using information from the missing values, 'informative missing', produced a better fitting model.

The Q classification is an ordinal scaled variable; herein, we opted to not use the 'ordinal restricts order' option allowing unordered splits on this variable.

A total of 110 papers (30% of the observations) were randomly selected and placed in a validation set; 229 papers served as the training set. This cross-validation approach guards against creating an overly complex model (overfitting a model) that would not perform well when applied to new data. With cross-validation, we built a model on the training set and then applied the same model to the validation set to evaluate its performance. After 10 splits, the model had an R^2 value of 0.188 for the training set and 0.044 for the validation set. Ten was the number of splits that maximised the R^2 for both the training and validation sets.

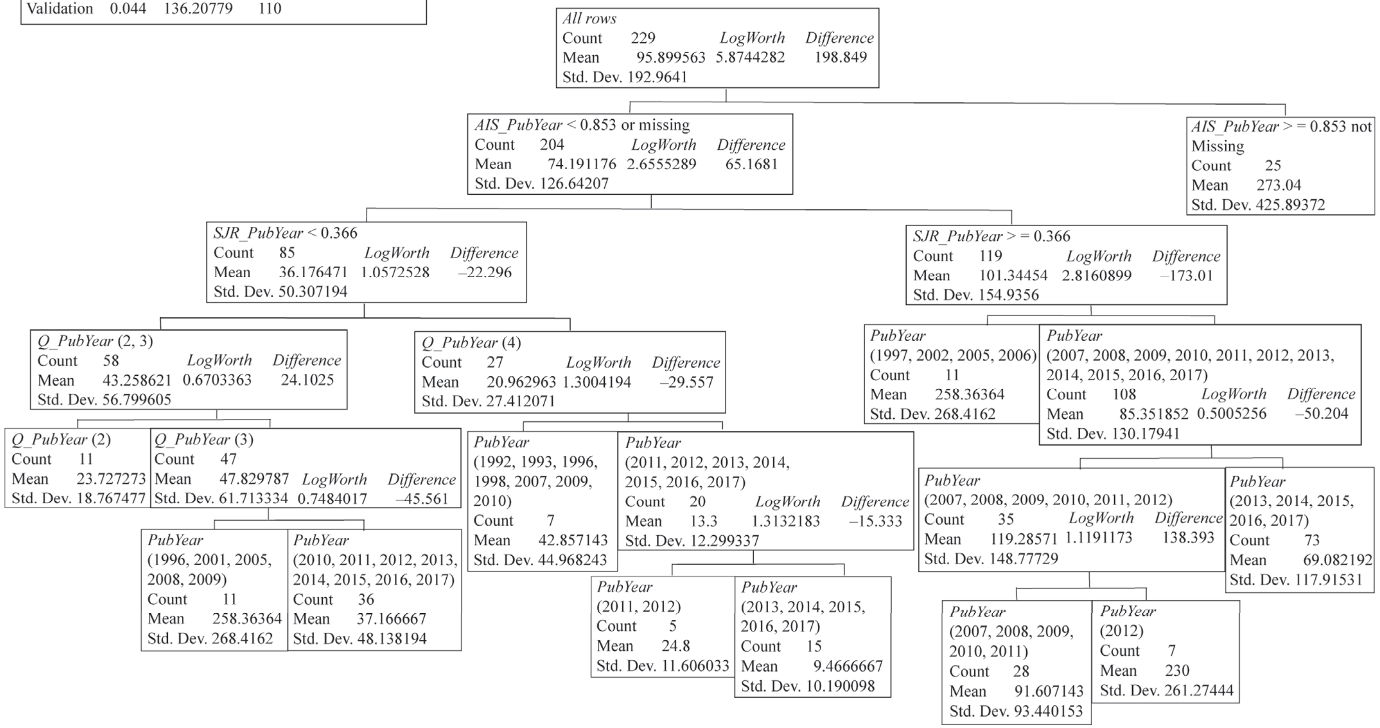
The first split was observed at an AIS value of 0.853 of the journals. If a journal had an AIS value equal to or greater than 0.853, the predicted average number of citations (in Google Scholar) was 273. When we examined the importance of the predictors, the variables that contributed the most to the predictive model were led by the AIS quality measure of journals, followed by the number of years since publication and the SJR measure of the journal. The Q category of the journal and the journal category (such as IT or engineering) did not matter much in collecting citations.

[1] JMP® Pro 16.2.0 was used for all subsequent analyses; for technical details, please see *Grayson–Gardner–Stephens* [2015].

[2] LogWorth is the adjusted *p*-value transformed to a log scale: −log10 (adjusted *p*-value). The bigger the LogWorth value, the better the split is.

Figure 10. Regression tree with number of citations as response

	R^2	RASE	N	Number of splits	AICc
Training	0.188	173.52609	229	10	3,036.92
Validation	0.044	136.20779	110		



Note. RASE: median of root average squared error; AICc: Akaike information criterion for small sample sizes; PubYear: publication year (the number of years a paper was available).

Decision tree models can be enhanced in two ways: bagging and boosting. Bootstrap aggregation or bagging can be used to average bootstrap samples drawn from data. Bootstrap samples are samples of the same size as the original data but are drawn with replacement (i.e., an observation may not be sampled at all or could be sampled several times). The bootstrap aggregated model is the average of all models generated from the bootstrap samples. Boosting is an additive modelling approach in which a sequence of low-complexity models is built with each model successively predicting more of the remaining residual error.

To illustrate and check the stability of the variable contributions, we used both approaches. (See Figures 11 and 12.) The important takeaway seems to be that the AIS of the journal and the publication year (in other words, the number of years a paper was available) are the two most important determinants (55-68%) of a paper's impact.

4. Discussion

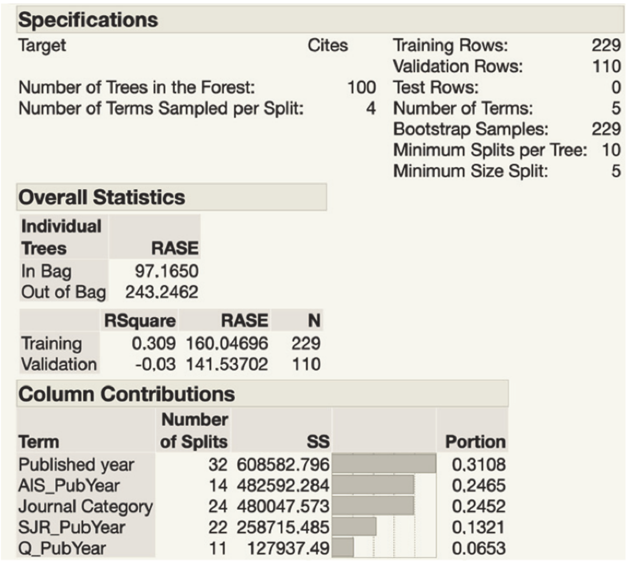
*RQ*1: *How has the number of MM articles published across SJR quartiles changed over the years?*

Since 2005, the number of published MM articles has increased; this finding is consistent with those of *Wendler* [2012], *Santos-Neto–Costa* [2019], and *Monteiro–Maciel* [2020]. However, our analysis also shows that higher-ranked journals (Q1) do not immediately respond to growth, increasing only in 2008. Since 2014, Q1 journals have been on a declining trend possibly because of the realisation of the need for MMs as a scientific instrument requiring more rigor. Nevertheless, the reception of MMs within other quartiles is increasing. A new study covering the latest data is needed to test whether this trend has continued since 2018.

*RQ*2: *How are published MM articles distributed across different journal categories?*

Consistent with the findings of *Santos-Neto–Costa* [2019], our findings show that IT journals dominate the publication of MM articles. Additionally, our analysis indicates that IT journals across all quartiles are receptive to MM articles. It will be interesting for future research to perform an in-depth analysis to determine whether the quality of MM articles published across different quartiles of IT journals differs with the set criteria. Engineering and operations/SCM journals form the second tier in terms of receptiveness towards MM articles. However, proportionately fewer Q4 journals within these two categories have attracted MM articles. Capability domains within finance are a potential opportunity for MM articles to penetrate as currently only a very few finance journals have published MM articles (given the high volume of finance journals).

Figure 11. Bootstrap forest with number of citations as response (screenshot)



Specifications

Target	Cites	Training Rows:	229
		Validation Rows:	110
Number of Trees in the Forest:	100	Test Rows:	0
Number of Terms Sampled per Split:	4	Number of Terms:	5
		Bootstrap Samples:	229
		Minimum Splits per Tree:	10
		Minimum Size Split:	5

Overall Statistics

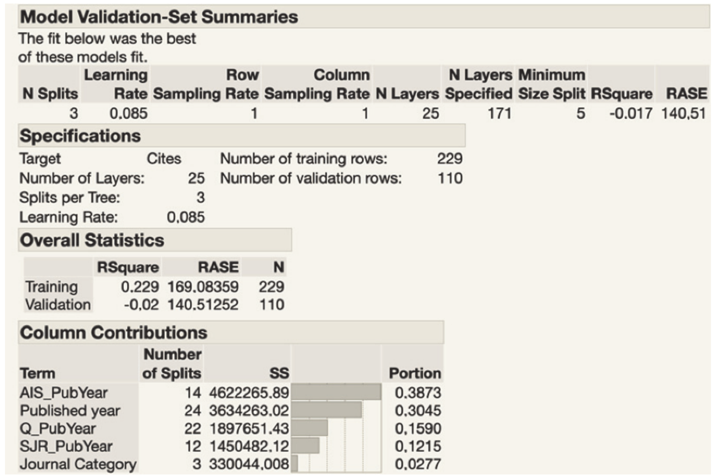
Individual Trees	RASE
In Bag	97.1650
Out of Bag	243.2462

	RSquare	RASE	N
Training	0.309	160.04696	229
Validation	-0.03	141.53702	110

Column Contributions

Term	Number of Splits	SS	Portion
Published year	32	608582.796	0.3108
AIS_PubYear	14	482592.284	0.2465
Journal Category	24	480047.573	0.2452
SJR_PubYear	22	258715.485	0.1321
Q_PubYear	11	127937.49	0.0653

Figure 12. Boosted tree with number of citations as response (screenshot)



Model Validation-Set Summaries

The fit below was the best of these models fit.

N Splits	Learning Rate	Row Sampling Rate	Column Sampling Rate	N Layers	N Layers Specified	Minimum Size Split	RSquare	RASE
3	0,085	1	1	25	171	5	-0.017	140,51

Specifications

Target	Cites	Number of training rows:	229
Number of Layers:	25	Number of validation rows:	110
Splits per Tree:	3		
Learning Rate:	0,085		

Overall Statistics

	RSquare	RASE	N
Training	0.229	169.08359	229
Validation	-0.02	140.51252	110

Column Contributions

Term	Number of Splits	SS	Portion
AIS_PubYear	14	4622265.89	0.3873
Published year	24	3634263.02	0,3045
Q_PubYear	22	1897651.43	0,1590
SJR_PubYear	12	1450482.12	0,1215
Journal Category	3	330044,008	0,0277

*RQ*3: *What is the distribution of MM articles across journals and how are these journals ranked?*

There is no journal that publishes a high volume of MM articles other than the *Software Quality Journal* (17 MM articles in total), and only six journals have published more than five MM articles. This indicates a high level of spread (339 MM articles across 193 journals) and implies that MM articles still have the potential to grow in number. Although the criticism over the rigor of MMs is intense, it is not visible in the analysis that only lower-ranked journals favour MM articles. Furthermore, the average net SJR over the period indicates that most of the journals increase their ranking during the period in which they publish MM articles.

Amongst the top 50% of business journals listed within Scimago, only 18% published MM articles from 1973 to 2017. Although the number of published MM articles has been on the rise since 2008, they have not yet evolved to become a fully accepted measurement instrument to gauge organisational capabilities. Different ranking groups (deciles within Q1 and Q2) have published different numbers of MM articles, and it appears that publishing within deciles with higher volumes of MM articles attracts a higher average number of citations. However, no MM article has been published in any of the top decile journals within Q1. This creates an opportunity to understand what it takes to publish an MM article in a journal that belongs to the top 10% of Q1 journals (top 2.5% of all business journals).

*RQ*4: *Does publishing in higher-ranked journals result in more citations?*

Results from various partitioning models (regression tree, bootstrap forest, boosted tree) confirm what seems to have been the generally accepted anecdotal evidence: publishing in top journals will have the greatest impact, and the AIS measure of journal quality seems to be a good predictor.

5. Conclusion

This review is based on an analysis of 339 MM papers published in 193 journals between 1973 and 2017. It presents a descriptive analysis providing multiple insights into the distribution of volumes of MM articles published across journal categories and journal ranks. Further, it explores possible answers to the question ‘where to publish to achieve the maximum impact’ using inferential statistics.

Although MMs have been heavily criticised for their rigor, related articles have been published somewhat evenly across all journal ranking levels. The very top-ranked journals have not been interested in MM articles, and there might be a trend amongst the top journals to publish fewer MM articles; this topic requires further investigation. Only 18% of the top 50% ranked journals have published MM articles, and only six journal categories account for the publication of 80% of MM articles, thus indicating the potential of MMs to grow as a credible measurement instrument. There is a high chance of attracting more citations when an article on MM is published in higher-ranked journals and in journal rank deciles that have already published high volumes of MM articles.

We can only speculate that replacing Google Scholar citation data (a noisy measure) with Web of Science citations will strengthen the message of 'publishing in top journals'.

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