\chapter{Introduction}

\label{chap01}

This chapter describes the background, objectives, contributions, and structure of this study.

\section{Background and Objective}

In the modern era, to cope with the increasing complexity and scale of scientific research problems, multiple researchers are now working together, and sharing research problems and results has become essential. For this purpose, various means of scholarly communication have been proposed and utilized. For example, academics established academic journals and conferences as standard scholarly communication methods in the past few decades. The number of media and events for such communication has grown to a vast number and scale. In this climate, academic research has been shared and disseminated mainly within the academic community.

Recently, however, there has been much talk about rethinking the value of scientific research. In the past, the research value was assessed by the researcher's discovering and creating unknown knowledge and the direct stakeholder's utilizing the research results to create secondary value. The value of research given in this way reflects only the perspective of a narrow community of stakeholders, which may diverge from the socially accepted notion of research value. Such a phenomenon can interfere with empathy between the academic community and society and induce obstacles to scientific research's smooth planning and progress. For this reason, many have advocated the need to expand the scope of research evaluators and incorporate the perspectives of various members of society into the evaluation process. In response to this challenge, people are now focusing on various communication activities that reflect the social interest in research and the channels through which they appear. For example, in the mass media, scientific research has been communicated to the general public through newspaper articles and television broadcasts of news and documentaries. On the other hand, recently, with the activation of social networking services, stakeholders in research and non-specialists in research have been referring to research on various new platforms such as blogs, Facebook, and Twitter, accelerating the dissemination and discussion of scientific research in society\cite{57}.

There have been various attempts to estimate the effects of such broad science communication surrounding research. As academic publishing and communication moved online, Usage metrics based on downloads and views and Webometrics based on web links were proposed. Since 2010, the usefulness of Altmetrics, a new metric based on communication activities and interactions on various social media, has been proposed \cite{3}. The word "Altmetrics" is a combination of the words "alternative" and "metrics", although, in general, the issues and approaches addressed by Altmetrics are different from those of bibliometrics and are not alternative concepts\cite{2}. Altmetrics are often considered more transparent than bibliometrics and webometrics. They provide a quicker and more real-time view of impact, are accessible to all, cover non-academic audiences, and can encompass a wider variety of research outputs and sources\cite{4}. Altmetric Attention Score (AAS), a widely accepted Altmetrics provided by altmetric.com, offers a broad measure of an article's value by comprehensively considering the number of times an academic article has been mentioned in various communication sources, including social media.

On the other hand, as the Web and the media develop, various communication formats have emerged in academia. Also, in the early 2000s, electronic scholarly communication was proactively used in informal communication, cooperation, publication and dissemination of results, and relationship building among academics\cite{6}. The Web provides an opportunity to distribute and share a wide range of atypical content in science. The use of non-standard electronic media such as diagrams, presentations, and videos is increasing in research and education. Among them, communication using online academic videos, a relatively new method, has been recognized as valuable because of its ease of dynamic expression compared to other media. For example, online video could be utilizable in the arts and humanities, such as dance and film, where human motion is essential\cite{6}. Video recordings of elaborate scientific research demonstrations, scientific documentaries, and lectures may be more effective than text for explaining the scientific experience. For example, online videos can effectively communicate scientific methodologies, protocols, research results, and market educational and volunteer activities\cite{7}. In response to reports of the effectiveness of such online video-based scientific communication, the use of online video is expanding in academia as well. For example, Nature and Cell proactively encourage accepted papers to submit videos introducing the research topic and results, published in a dedicated section for online videos on the journal's website. Also, Journal of Visualized Experiments, a journal for experiment videos mainly in life sciences, has pioneered and established a new journal format, the online video journal. Also, some conference proceedings, mainly in the media field, hold presentations focusing on video works.

Furthermore, online academic videos are not limited to the academic community, actively emerging on popular platforms, such as YouTube, founded in 2005 and the second most visited website in the world after Google\cite{8}. It is the second most visited website in the world after Google. While people mainly use YouTube for entertainment purposes such as music and comedy, some academics have been distributing their academic work online since the foundation of YouTube. For example, videos of renowned scientist Stephen Hawking's lectures on the universe (youtube.com/watch?v=xjBIsp8mS-c) and a physics lecture recorded at MIT (youtube.com/watch?v=sJG-rXBbmCc), both released online shortly after the foundation of YouTube, have been viewed about 6.5 million times and 5 million times, respectively. For another example, Science, a well-known academic journal, has been running a YouTube channel since 2008 and has released videos introducing some of the research published in the journal. Such efforts enable the journal to produce and distribute videos to explain and socially disseminate complex research to those involved.

With these reports on the use and effectiveness of online academic videos, video production and publication are becoming a worthy investment of research resources for academics. For videos that mention the URL of Science journals on YouTube, Fig\ref{fig1-1} shows the estimated number of newly released videos that mention articles on Science magazine and other videos related to Science. The number of videos mentioning articles is the number of results obtained by searching YouTube queries in the literature browsing domain (science.sciencemag.org/content), and the number of other videos is the balance between the number of videos searched in the main page domain (science.sciencemag.org) and that of videos mentioning the articles. The figure implies that the numbers of videos mentioning articles and other videos related to Science on YouTube have been increasing trendily since the foundation of YouTube until the most recent year, 2019.

\begin{figure}[tbp].

\begin{center}

\includegraphics[width=10cm]{pics/fig1-1.jpg}

\end{center}

\caption{Estimated number of new YouTube videos mentioning Science Magazine}

\label{fig1-1}

\end{figure}

However, the research on the impact of online academic videos on the value of research, which is essential in investing in video production, is scarce. If the impact of online academic videos on research value, i.e., the citation count and public attention level, is proved, it could provide a rationale for investing in video production of research resources. On the other hand, understanding the differences in academic video's impact by the research attributes, such as the field, researchers, or publication sources, could support understanding what kind of research and video can effectively contribute. Thus, understanding the interaction between research and online academic videos is crucial in designing effective communication through academic videos. Furthermore, if it is possible to classify online academic videos, which are an atypical communication method, by extracting their characteristics, making proposals on the content of videos for effective communication will be possible.

In this study, we propose a method to assess academic videos' impact on academic papers' citation counts and Altmetrics. Specifically, we prepare a large dataset of academic articles in specific research fields and collect YouTube videos that mention the articles in the title or description as article-mentioning-videos. As a control group for the articles with mentioning-videos, we sample the articles without mentioning-videos with the same quality as the articles with mentioning-videos using our original homogenization method. We then test for the difference in the populations of origin for the citation count and AAS distributions of the two article groups to verify article-mentioning videos' effectiveness. Next, based on the qualitative analysis of the large number of academic videos collected, we define the taxonomy of "the purpose of article-mention" for the video method and identify the effective video method by comparing the distribution of the citation counts and AAS among the articles with mentioning-videos divided along with the label. Finally, we propose the "YouTube score," an article index representing the article's popularity on YouTube and verify that the YouTube score is a leading indicator that saturates earlier than the citation count. We then perform a regression analysis between the YouTube scores and the citation counts for article groups mentioned by each video group divided by the video method, followed by identifying the video group that shows a significant correlation, estimating its label as an effective video method for predicting the future the citation counts using the YouTube scores. This method allows researchers to predict future the citation count from the YouTube scores of articles and evaluate the academic impact of articles in the early stage of publication.

To evaluate the proposed method, we conducted experiments using academic article datasets in two broad fields: mathematics & computer sciences and life & earth sciences. We sampled the papers without videos against the papers with videos and tested that the citation counts and AAS distributions between the two groups originated from different populations, finding a significant effect of article-mentioning-video. Also, categorizing videos by labelling the purpose of article-mention, we confirmed the differences in the citation counts and AAS distribution by the video method and identified the effective video methods for each indicator. Furthermore, we verified that the YouTube score saturated earlier than the citation count and extracted some video methods with a significant correlation between the YouTube score and the citation count, suggesting the possibility of predicting future citation counts based on the YouTube score of early-stage papers.

Using this method, researchers can allocate limited research resources to video production and video design based on quantitative evidence. Furthermore, it is possible to predict the citation counts in the future based on the YouTube score by releasing YouTube videos in the methods with significant prediction accuracy for papers in the early stages of publication, which will accelerate the evaluation of research stakeholders and help build a research portfolio.

\section{Contributions}

The results of this study allow the followings.

First, this study was able to verify and quantitatively analyze that YouTube videos mentioning academic literature have a significant impact on the citation counts and Altmetrics of the literature. The results verified that science communication on YouTube contributes to the research's academic and social attention and made it possible to evaluate the effect of such communication quantitatively.

Next, we proposed a taxonomy of the purpose of article-mention on YouTube and quantitatively analyzed and compared distributions of the citation counts and Altmetrics for each article group divided by the videos' labels. The results allow us to provide a quantitative ground for selecting video methods that could more effectively contribute to the article's citation count and Altmetrics.

Finally, we verified that the YouTube score, a proposed measure of the popularity of an article on YouTube, is a leading indicator that saturates earlier than the citation count. As a result of the regression analysis between the two indicators, we identified the labels that showed a significant correlation between them. The results enable us to estimate the video method that effectively predicts future citation counts using the YouTube score for articles in the early stages of publication.

Based on the above, the contribution of this study can be summarized as follows.

\begin{itemize}

\item We verified that article-mentioning YouTube videos influence the article's citation count and Altmetrics based on quantitative analysis.

\item We confirmed the differences in the video's impact on the citation count and Altmetrics by the purpose of article-mention and identified effective methods.

\item We proposed an indicator for the article's popularity on YouTube and partially estimated the video method that effectively predicts the future citation count using the indicator for articles in the early stage of publication.

\end{itemize}

\section{Structure}

Chapter 2 provides the related works and significance of this study. Chapter 3 presents our method for verifying and measuring YouTube videos' impact on the citation counts and Altmetrics of papers and predicting the citation counts using the videos. Chapter 4 describes the dataset used in the experiment and show the experimental results of the method proposed in the previous chapter. In Chapter 5, based on the results, we discuss the trends of article-mentioning videos on YouTube and some notable points when using our proposed method. Chapter 6 presents the conclusions and future works of this study.

\chapter{Related works}

\label{chap02}

This chapter describes related studies and discusses our study's position and significance to measure the impact of article-mentioning videos on YouTube using our proposed method. To be specific, we first describe previous studies on various factors that affect the popularity of science communication on YouTube and then discuss the need to consider video methods in this study. Next, we explain the previous studies on the impact of non-standard science communication on scientific research, the ground for understanding article-mentioning videos' impact on YouTube on the citation counts and Altmetrics of articles.

\section{Popularity Factors of Science Communication on YouTube}

\label{sec2-1}

The extent to which a YouTube video influences society depends on the popularity of the video. Video communication for professionals using YouTube is an emerging method, and research on the factors that influence its popularity is relatively scarce. However, science communication as entertainment targeting non-experts has become an established genre of YouTube videos, and many studies have addressed the popularity of such videos. This section describes existing research on factors that influence the popularity of professional and non-professional science communication videos on YouTube.

First, in terms of content-agnostic factors, the study by Burgess\cite{22}, Juhasz\cite{23}, Yoganarasimhan\cite{24} reported that the social network of science communication channels is a factor that influences the popularity of videos and channels. Crane et al. \cite{25} categorized science communication videos into three qualitative categories and found a unique distribution of view history from each category, indicating that the video's quality affects the growth of view counts. Furthermore, Figueiredo et al.\cite{26} confirmed that the high-quality video group in Crane et al.'s study generated a large number of new views over a period ranging from a day to a week, while the other groups recorded multiple small peaks of new views. This phenomenon is related to the 'rich-get-richer' effect in the YouTube video recommendation system and the channel's social network\cite{21}. However, some channels do not disclose their 'friends' or 'featured channels' lists, and it is challenging to render networks between YouTube and SNS platforms explicitly, which pose a significant challenge to the analysis of social networks surrounding\cite{24} YouTube. Although social network analysis for science communication channels is outside this study's scope, it is essential for a general understanding of YouTube channels' popularity.

On the other hand, the videos' content factors are most likely to explain their widespread popularity mechanism in the YouTube community\cite{21}. Widespread popularity here refers to popularity among audiences of all backgrounds, as opposed to tiny popularity among niche audiences. Figueiredo et al.\cite{26} showed that videos dealing with topics and content that attracted more participants represented the tendency of higher popularity. Therefore, in understanding the factors that determine the popularity of a video, it is essential to consider the video's content factor.

Many studies on science communication on YouTube focus on evaluating the veracity of information, and some confirmed the tendency of some topics to influence the popularity of videos. Keelan et al.\cite{28} classified the tone of 153 videos about immunization into positive, ambiguous, and negative, and found that negative videos received more views and ratings than positive videos, even though 45\% of negative videos contained misinformation. On the other hand, Sood et al.\cite{29} analyzed 199 videos about kidney stones and reported that videos that contained misleading information received higher view counts than those that did not. Other studies have not found a statistically significant difference between view counts or ratings of a video and its content veracity.

Furthermore, the type of channel has also attracted attention from studies on the popularity of YouTube videos. Professionally generated channels (PGC) for commercial marketing are likely to have richer economic resources than general User-generated channels (UGC), and Kim\cite{34} pointed out that the mass production of high-cost videos released by PGCs could disrupt the UGC community. However, determining a video's content is subject to the video's views and appeal rather than the number of videos on the channel, so the channel must still deliver content that is of interest to the YouTube community\cite{21}. Although the evidence is weak, there are some claims that UGC is more popular than PGC: Lorenc et al.\cite{35} examined the top 241 channels in terms of the number of subscribers and found that UGC delivered up to 68\% of the videos, and the only video genre that had more PGC videos was music. In terms of science communication videos, Lo et al.\cite{36} examined videos on epilepsy and found that UGC content is more predominant in views, comments, ratings, and especially in comments than PGC, suggesting that UGC has more active communication between video producers and viewers than PGC. Welbourne et al.\cite{21} analyzed 39 science communication channels with the highest popularity and found that PGC had the highest number of videos, but UGC was dominant in overall popularity. Meanwhile, regardless of PGC or UGC, quick delivery of information or fixed speaker significantly contributed to the view counts.

\chapter{Proposed Method}

\label{chap03}

This chapter explains our proposed method for verifying the video's impact on the citation counts and Altmetrics, identifying effective video methods, and predicting the citation counts of articles using videos' popularity.

First, we obtain the data of YouTube videos mentioning the article set and conduct a controlled experiment on the citation counts and AAS distributions by setting up two groups of papers: those with videos and those without videos, paying attention to homogenization. Next, we split the video set by the taxonomy of the purpose of article-mention and identify the effective video methods by comparing the citation count and AAS distributions of the articles mentioned by each video group. Finally, we verify that the popularity of articles on YouTube is saturated in the early stage of publication using our novel indicator and assess the predictability of the citation counts based on the regression analysis of the indicator and the citation count, followed by estimating the effective video method for prediction.

\section{Overview of the method}

\label{chap3-1}

\begin{figure}[tb]

\begin{center}

\includegraphics[width=15cm]{pics/fig3-1.png}

\end{center}

\caption{Overview of the method}

\label{fig3-1}

\end{figure}

Fig\ref{fig3-1} shows an overview of the proposed method in this study. The first step is to prepare an article dataset by collecting article data in a specific research field and publication period. Next, we acquire a video dataset by retrieving YouTube videos that mention the obtained articles and consider the articles mentioned by videos as the articles with videos(i).

Then we sample the articles without videos and conduct a controlled experiment on the citation count and AAS distribution of the two papers groups(ii). For sampling the papers, we use the homogenization method to control other variables that could affect the citation count and AAS.

Next, we assign labels to the videos according to the taxonomy of the purpose of article-mention and compare the distributions of the citation count and AAS for papers corresponding to each video groups split by the labels, confirming the differences in the effects of the video methods and identifying the optimal video method for each paper index(iii). Labels are assigned based on a qualitative analysis of what message about the mentioned article a video delivers to viewers by observing the video's content.

Finally, to predict an article's future academic impact using the video's popularity, we proposed the YouTube score calculated by view counts of the videos and verified that the YouTube score is saturated earlier than the citation count. Then we evaluate the predictability of the citation count based on the correlation coefficient between the YouTube score and the citation counts in each paper group split by the videos' purposes of article-mention and identify the effective video method for predicting the citation counts(iv).

\section{Details of the method}

This section describes our proposed method in more detail.

\subsection{Dataset}

The datasets comprise two subsets: article datasets and video datasets. For the article dataset, we obtain articles in specific research fields. Next, to obtain the video data, we use the article's metadata as keywords to query YouTube videos that mention the articles using Google API.

\subsection{Validation of the impact of article-mentioning videos}

Next, we verify the videos' impact on the citation counts and AAS of obtained articles. First, we test normality for distributions of the citation count and AAS of both article groups with and without videos sampled by the homogenization method, followed by a t-test to validate the impact.

\subsubsection{Homogenization method}

In verifying the video's impact on the citation count and AAS, it is necessary to control the variables other than the video's presence. We apply conditions on the article's metadata and match the articles with and without videos that satisfy all proposed conditions. This section explains the homogenization method in detail.

(i) Splitting the articles dataset by the presence of video

We split the dataset into two groups by the presence or absence of videos: the articles with videos and the candidate articles without videos.

(ii) Sampling the articles without video

We match each article with videos against the articles that satisfy all the homogenization conditions sampled from the candidate articles without videos. Specifically, we sample a single unmatched article with videos and extract the papers that satisfy all the conditions shown in Table\ref{tbl3-1} in the candidate articles without videos, creating a matching candidate list. If the number of candidates is less than the sampling size $m$, we abandon matching and exclude the article of interest from the articles with videos; Otherwise, we sample $m$ papers from candidates, including them in the articles without videos.

\begin{table}[htbp]

\begingroup

\renewcommand{\arraystretch}{1.1}

\caption{Homogenization conditions}

\label{tbl3-1}

\begin{center}

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\begin{tabular}{p{0.17\linewidth}p{0.25\linewidth}p{0.5\linewidth}}

\noalign{\hrule height 1.0pt}

Condition&Description&Action(Scopus) \\

\noalign{\hrule height 1.0pt}

Source&Identical publication source&Match \textless Source title\textgreater property\\

Document type&Identical document type&Match \textless Doctype\textgreater property \\

Last author&Identical last author&Split \textless Author(s) ID\textgreater value by semicolon(;) and match the last value \\

Funded&Presence of fund&Match whether \textless Funding Details\textgreater property is NaN \\

\noalign{\hrule height 1.0pt}

\end{tabular}

}

\end{center}

\endgroup

\end{table}

(iii) Determining the articles with and without videos

If any article in the articles with videos remains not matched, (i) is executed. Otherwise, we complete sampling and determine the two sets of articles for the experiment.

\subsubsection{Test for the citation count and AAS distribution for both groups of articles}

We conduct a control experiment on the articles with and without videos to verify the video's impact. Specifically, we first test the normality of the logarithmic distribution of the citation counts and AAS of both groups of articles, using D'Agostino's $K^2$ test\cite{54,55,56}(hereafter Normaltest). In Normaltest, samples out of the range of \ref{eq3-7} in the distribution are considered outliers and excluded.

Next, we perform Student's t-test on distributions of both article groups. By testing that the two distributions do not originate from the same population, we show that video has a significant impact on the citation count and AAS. Simultaneously, we confirm that the mean value of the distribution is higher in the articles with videos than in the articles without videos, indicating the contribution of video to the citation count and AAS.

\subsection{Comparison of the video's impact by article-mention purpose}

After identifying significant differences between the citation counts and AAS distributions, we compare the video's impact on the citation count and AAS by article-mention purpose and then clarify each index's effective video method.

\subsubsection{Taxonomy of the article-mention purposes}

\begin{table}[htbp]

\begingroup

\renewcommand{\arraystretch}{1.1}

\caption{Taxonomy of the article-mention purposes}

\label{tbl3-2}

\begin{center}

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\begin{tabular}{p{0.18\linewidth}p{0.18\linewidth}p{0.25\linewidth}p{0.30\linewidth}}

\thickhline

Label & Purpose & \begin{tabular}{p{\linewidth}}Conditions\\ (Must satisfy one or more)\end{tabular} & \begin{tabular}{p{\linewidth}}Example\\ (Video ID)\end{tabular} \\ \thickhline

\begin{tabular}{p{\linewidth}}News\end{tabular} &\begin{tabular}{p{\linewidth}} Publication announcement and dissemination \end{tabular}&\begin{tabular}{p{\linewidth}} Playtime for article-mention is less than 3 minutes \end{tabular}& \begin{tabular}{p{\linewidth}}・Preview or review of the article\\ (ID: uA7HX7URCF8)\\ ・Introduction to the project to which the article belongs\\ (ID: nsRLpyDZsog)\end{tabular} \\ \hline

\begin{tabular}{p{\linewidth}}Explanation \end{tabular} &\begin{tabular}{p{\linewidth}} Explanation of the contents of the paper \end{tabular}&\begin{tabular}{p{\linewidth}} Notice of the explanation of the article in video description or audio \end{tabular}& \begin{tabular}{p{\linewidth}}・Presentations to academics\\ (ID: QeMgkYM7sMk)\\ ・Assessment of specific contents of the article\\ (ID: ouGtd8nhm6Y)\\ ・Presentation of unique products that utilize the methods of the article\\ (ID: 4l2Ufx-Iz6U)\end{tabular} \\ \hline

\begin{tabular}{p{\linewidth}}Reference\end{tabular} & \begin{tabular}{p{\linewidth}}Reference for the basis of claim or topic\end{tabular} &\begin{tabular}{p{\linewidth}} Stated as a reference in description \end{tabular}& \begin{tabular}{p{\linewidth}}・Unclear article-mention part\\ (ID: fi3AROm4ZGg)\\ ・Difficult to classify any other way\end{tabular} \\ \hline

\begin{tabular}{p{\linewidth}}Supplementary\end{tabular} &\begin{tabular}{p{\linewidth}} Supplement to the content of the article \end{tabular}& \begin{tabular}{p{\linewidth}}・States YouTube link in the article\\ ・Identical to the supplementary video on journal website\\ ・Original or animated data in the article\end{tabular} &\begin{tabular}{p{\linewidth}} (ID: P6lBkK3J9wg)\end{tabular} \\ \thickhline

\end{tabular}

}

\end{center}

\endgroup

\end{table}

First, we define a taxonomy of the article-mention purposes and assign a label to each video. The taxonomy partly refers to the classification of video purposes proposed by Thelwall et al.\cite{51}, but we modified and summarized it, considering the videos that cannot be reasonably classified. Table\ref{tbl3-2} shows the taxonomy in detail, suggesting an example video of each case.

\subsubsection{Comparison of video's impact by video methods}

After labelling videos with article-mention purpose, we split the article dataset by the labels. Next, we compare each group's mean citation count and AAS to identify which video methods effectively contribute to each index. Note that an article mentioned by multiple videos with different labels belongs to multiple article groups, in which case we give the raw citation count and AAS to each group.

\subsection{Predicting the citation count using the article-mentioning video's popularity}

As a measure of the article's popularity on YouTube, we propose the YouTube score, which comprises the view counts of article-mentioning videos. Next, we suggest a method for predicting an article's future citation count using YouTube score and identify the video methods that are effective for prediction.

The view count of a video is the most intuitive indicator of the popularity of a YouTube video, and the relationship between the view count and the citation count of the article mentioned by the videos is an interesting issue. However, there has been no quantitative analysis of the view counts of YouTube videos and the articles' citation counts. In terms of the article's social popularity, on the other hand, Altmetrics tend to saturate earlier than the citation count\cite{43,52}. Also, for 90\% of YouTube videos, the growth model of the view counts can empirically be approximated to a saturation model using a sigmoid function\cite{60}. Considering that Altmetrics immediately captures the activities on social media, and YouTube shares various social media characteristics, it is reasonable to assume that the popularity of science communication on YouTube has characteristics similar to those of Altmetrics. Such assumption allows us to expect high future citation rates for high-quality articles if the article-mentioning videos show significant popularity in the early stage of publication.

Therefore, we first observe that the YouTube score saturates earlier than the citation count for the articles published in prominent journals and conference proceedings in a particular research field. Then, we evaluate the predictability of future citation counts for the articles in the early stage of publication using the YouTube score and identify the video methods for the validity of prediction.

\subsubsection{Observing saturation of article-mentioning video's popularity}

We calculate an indicator that captures the popularity of science communication about target article on YouTube based on view counts of videos mentioning the article, naming it the YouTube score. The article's YouTube score $YTscore$ is defined as in \ref{eq3-1} using $(viewcount)\_i$, the view count of article-mentioning video $i$.

\begin{equation}

\centering

\label{eq3-1}

YTscore = \log\_{10} \sum\_{i} (viewcount)\_i

\end{equation}

We then observe that the YouTube score of an article saturates earlier than the citation count. An ideal way to achieve this would be to analyze each indicator's increase rate over time, using time series data of videos' view counts and article's citation count. This study, however, does not focus on individual articles but rather on comparative analysis between article groups to detect significant differences. Therefore, we use the datasets of articles and videos published in the pre-period, when enough time has passed since the publication and the citation count has grown sufficiently, and the datasets of papers and videos published in the post-period, when we expect the citation count to grow in the future.

In this method, we assume that the sample population of the articles' citation counts and the YouTube scores originates from a specific population for the articles published in the most renowned journals and conference proceedings in the same field. Then, as shown in Fig\ref{fig3-2}, we assume that the population grows toward a particular probability distribution depending only on the elapsed time since the publication of the articles and that the growth curve has an S-shape. The growth model is assumed to be invariant regardless of the publication period of the articles. Given the article groups in the pre-period and the post-period, if the two distributions of an article index are statistically fit, the index's distribution in the post-period is considered "saturated", implying that there has been no significant change in the population of the index since the post-period. On the other hand, if the distributions are statistically not fit, we consider the index's distribution in the post-period "growing" and determine that the article index in two article groups originates from significantly different populations.

\begin{figure}[tbp]

\begin{center}

\includegraphics[width=14cm]{pics/fig3-2.png}

\end{center}

\caption{The Growth Model of Population of an Article Index's Distribution}

\label{fig3-2}

\end{figure}

Given the above assumptions, we first test the goodness of fit against the YouTube score and the citation count distributions of the articles with videos in the two periods to examine the saturation or growth in the post-period distribution. If there is significant goodness of fit between the two periods, we consider both distributions to originate from the same population, suggesting that the index in the top-renowned sources saturates in the post-period. On the other hand, if the test finds no goodness of fit, we consider that both distributions originate from different populations, and the index is growing in the post-period. If the test suggests that the citation count is growing while the YouTube score saturates for the post-period articles, we conclude that the YouTube score saturates earlier than the citation count.

We use Kolmogorov-Smirnov test\cite{62,63}(hereafter KStest) for testing goodness of fit. We excluded outliers from the YouTube score and the citation count distribution with the same criterion of Normaltest(Equation\ref{3-7}).

\subsubsection{Identification of video methods effective in predicting the citation count using the video's popularity}

If the test confirms the YouTube score's saturation and citation count's growth in the post-period, we split the pre-period article dataset by the video's label. Next, we perform a linear regression on the YouTube score and the citation count for each article group and evaluate the correlation coefficient. If the correlation is significant for a particular group, we conclude that predicting the future citation count by the YouTube score based on the videos with the same method is valid for the post-period articles. We consider the correlation coefficient of 0.35 or higher to be significant in this study.

On the other hand, an academic video's purpose and topic are essential factors in understanding the target audience's characteristics and the expected impact. Thelwall et al.\cite{51} examined 100 randomly sampled videos and the top-viewed 100 videos among 4282 YouTube videos tweeted by 589 academics and qualitatively classified the videos by their purpose, format, and related fields. Figure\ref{fig2-1} shows the classification of the video's purpose and number belonging to it, which is closely related to the method proposed in this study. The figure suggests that the videos' most predominant purpose is public dissemination in top-viewed videos and scientific demonstration in random videos, while education videos are relatively popular in both. The study concludes that the most popular videos are mainly processed videos targeting public audiences, but since the audience for most academic videos is very small, it is not reasonable to produce videos for the sole purpose of obtaining views.

Based on the above, many academic video producers seem to distinguish between experts and non-experts in terms of the intended video audience. Since the videos in this study clearly state the article in the title or description, the video producers may be aware of the experts or authorities in scientific research. Based on the classification of the purpose of science communication videos proposed by Thelwall et al.\cite{51}, this study proposes a taxonomy of the purpose of article-mention that identifies what effect the videos intends on viewers by mentioning articles. Using this taxonomy, we will clarify how the impact on the citation counts and AAS differ depending on the video's purpose.

\section{The Impact of Informal Science Communication on the Impact of Scientific Research}

This section describes the studies on various informal science communication's influence on scientific research's academic and social impact.

\subsection{Online Academic Videos}

Many TED talk videos deal with scientific and technical topics and are considered an effective means of science communication\cite{37}. Sugimoto et al.\cite{38} revealed that the number of citation of a TED video hardly correlates with the video's view counts on YouTube or the TED website, suggesting that the impact of TED talks is more for the public domain than for academia. The analysis of TED talk presenter\s properties and their citation counts found that more than 77% of the presenters received more than the average citation count. The main reason for this is that 74% of the presenters are affiliated with research institutions in the top 200 universities worldwide, making them highly influential regardless of their TED talk.

Given the increasing efforts to video abstracts of scientific research, there have been discussions on their effect on the citation counts. A review article on video abstracts reported that the view counts of YouTube videos showed a moderate positive correlation with the view counts of the article and the videos on the journal website, also revealing an intensive positive correlation between the view counts of videos on the journal website and the article\cite{40}. Another study showed a weak positive correlation between the view counts of video abstracts and the number of full-paper views of scholarly literature, and a controlled study of 62 scholarly literature confirmed that there was no significant difference in the mean citation counts between the literature group with and without video abstracts\cite{41}. Following this work, a cohort study of 351 random articles without video abstracts sampled from seven years of New Journals of Physics publication reported that articles with video abstracts could expect 1.206 times higher citation counts than those without video abstracts.

Given the above, this study assesses the article-mentioning YouTube video's impact on the academic paper's citation count and Altmetrics. Specifically, we first use a homogenizing method to sample articles with videos of the same quality as the articles without videos, compare the citation count and AAS distribution of the two article groups to verify the effectiveness of publishing article-mentioning videos on YouTube. Furthermore, we split the articles with videos based on the proposed taxonomy of the purpose of article-mention and compare the citation counts and AAS distributions to identify which purpose is a proactive contributor to each article index.

\subsection{Other formats}

Among informal methods of science communication, the study on the video has been relatively rare. Therefore, it is advisable to refer to research on other methods to obtain hints on this research question's methodology. This section describes how the citation count is related to Twitter and Altmetrics.

Twitter is the most active science communication platform among social media, and relatively many studies have delved into the relationship between Twitter and article indices. Eysenbach\cite{43} analyzed tweets mentioning 55 articles in Journal of Medical Internet Research and citation data, finding that, about two years after publication, the articles with the highest tweet counts received about 11 times more citations than the articles with the lowest tweet counts. The study also stated that tweets within three days of publication could predict highly cited papers. A study on the relationship between Altmetrics and the citation counts of 2677 articles published in 10 ornithology journals showed that tweets could predict citation rates in the group of journals in the field of avian-ecology\cite{44}.

Altmetrics, which covers scholarly activities on various social media, is a quantitative research subject, although it often focuses on the act of measurement rather than scholarly impact and lacks theoretical background on the relationship with the citation counts\cite{45}. Note that the factors that lead to social media activity and citing academic literature are different, and research metrics based on social media should be complementary to the citation counts\cite{48}.

Among the various Altmetrics, AAS has recently become a popular research subject because of its usage in academia and the wide range of media and platforms it covers. A regression model of AAS and the citation counts states that an increase in AAS from 1 to 20 could accompany a citation increase from 2.6 to 5.5 for articles in ornithology journals with an impact factor of 1.84\cite{44}. Another analysis of ten years of academic papers on the topic of ecology and conservation found a significant correlation between AAS and the citation counts, weakening for more recent papers\cite{49}. A broad study that analyzed articles in 30 Scopus sub-subjects suggested that AAS could predict future citation counts in two years in some fields, with Mendeley reader count as a significant predictor\cite{50}. A recent study on articles published in dermatology journals in 2017 revealed that AAS showed a moderate positive correlation with the journal impact factor and a weak correlation with the citation counts, particularly the latter due to the time lag in the growth of AAS and citations\cite{52}.

Based on the works above, we propose an indicator based on view counts of the videos mentioning the article for predicting future citation count. In particular, we use the taxonomy of the purpose of article-mention described in \ref{sec2-1} to identify the labels that show high prediction accuracy. To be specific, we split the papers with videos based on the article-mention purposes and perform regression analysis on the citation counts and the proposed indicator for each paper group to specify the groups with significant correlation.

\chapter{Experiments and Results}

\label{chap04}

In this chapter, we conduct experiments based on the proposed method using multiple datasets.

\section{Experiment}

This section explains the experiment's purpose and outline and then describes the datasets and experimental conditions.

\subsection{Purpose of Experiment}

The purpose of the experiment is to verify the effectiveness of article-mentioning video's impact on the citation count and Altmetrics, to identify the video's purpose of article-mentioning with more substantial impact, to evaluate the predictability of the future citation count for articles in the early stage of publication using the YouTube score, and to identify the video method for effective prediction.

\subsection{Overview of Experiment}

Fig\ref{fig4-1} shows an overview of the experiment. The experiments are conducted for each task.

\begin{figure}[tb]

\begin{center}

\includegraphics[width=15cm]{pics/fig4-1.png}

\end{center}

\caption{Overview of Experiment}

\label{fig4-1}

\end{figure}

\subsection{Dataset}

We used four article datasets, each consisting of two research fields and two different publication periods, and four video datasets corresponding to each article dataset.

\subsubsection{Article Dataset}

\label{article-dataset}

We obtained the article datasets from Scopus. Table\ref{tbl4-1} gives an overview of the article datasets. We chose two broad research fields: mathematics and computer science(Math \& Computer), and life and earth sciences(Life \& Earth). The two research fields are from the five major fields presented in the Leiden Ranking\cite{61}, which is essentially a summarization of Web of Science categories. We compared categories in Scopus to those of Leiden Ranking and organized the fields similar to them. The general approach to science communication differs depending on academic disciplines\cite{58,59}, and by covering various research fields, we can expect to extract the differences between disciplines regarding the characteristics of science communication on YouTube. We use articles published in journals and conference proceedings highly renowned in each academic field. Therefore, we first select the sources of publication, obtain articles in specific publication periods, and acquire AAS assigned to each article.

\begin{table}[htbp]

\begingroup

\renewcommand{\arraystretch}{1.1}

\caption{Overview of Article Datasets}

\label{tbl4-1}

\begin{center}

\scalebox{1.0}[1.0] {

\begin{tabular}{p{0.27\linewidth}p{0.2\linewidth}p{0.14\linewidth}p{0.08\linewidth}p{0.12\linewidth}p{0.14\linewidth}}

\thickhline

Dataset & Field & Publication period & Total \# of articles & \# of cited articles(\%) & \# of articles w/ AAS(\%) \\ \thickhline

Math \& Computer 2014 & \multirow{2}{\*}{\begin{tabular}[c]{@{}l@{}}Mathematics, Computer science\end{tabular}} & 2014.01〜06 & 9598 & 9022(94.0) & 3303(34.4) \\

Math \& Computer 2019 & & 2019.01〜06 & 14533 & 13057(89.8) & 5612(38.6) \\ \hline

Life \& Earth 2014 & \multirow{2}{\*}{\begin{tabular}[c]{@{}l@{}}Environmental, Agricultural, Earth science\end{tabular}} & 2014.01〜06 & 7816 & 7481(95.7) & 3382(45.2) \\

Life \& Earth 2019 & & 2019.01〜06 & 7742 & 7228(93.4) & 4301(59.5) \\ \thickhline

\end{tabular}

}

\end{center}

\endgroup

\end{table}

(i) Selection of article sources

Table\ref{tbl4-2} outlines the selection of article sources obtained by entering a query from the Scopus source search page(scopus.com/sources.uri). We selected the sources with the highest CiteScore in the previous year of each target publication period. The number of sources was set to 160 for Math \& Computer and 60 for Life \& Earth, not to vary each article dataset's size.

\begin{table}[htbp]

\renewcommand{\tabcolsep}{2.5pt}

\begingroup

\renewcommand{\arraystretch}{1.1}

\caption{Overview of Sources}

\label{tbl4-2}

\begin{center}

\scalebox{1.0}[1.0] {

\begin{tabular}{m{0.27\linewidth}<{\centering}m{0.25\linewidth}m{0.14\linewidth}m{0.1\linewidth}<{\raggedleft}m{0.1\linewidth}<{\raggedleft}m{0.1\linewidth}<{\raggedleft}}

\hline

\begin{tabular}{p{\linewidth}}Dataset\end{tabular} & \begin{tabular}{p{\linewidth}}Subject area\end{tabular} & \begin{tabular}{p{\linewidth}}Source type\end{tabular} & \begin{tabular}{p{\linewidth}}Metrics for year\end{tabular} & \begin{tabular}{p{\linewidth}}\# of queried\end{tabular} & \begin{tabular}{p{\linewidth}}\# of selected\end{tabular} \\ \hline

\begin{tabular}{p{\linewidth}}Math \& Computer 2014\end{tabular} & \multirow{2}{\*}{\begin{tabular}{p{\linewidth}}Computer Science OR Mathematics\end{tabular}} && 2013 & 3201 & 160 \\

\begin{tabular}{p{\linewidth}}Math \& Computer 2019\end{tabular} & & & 2018 & 3427 & 160 \\

\begin{tabular}{p{\linewidth}}Life \& Earth 2014\end{tabular} & \multirow{2}{\*}{\begin{tabular}{m{\linewidth}}Agricultural and Biological Sciences OR Earth and Planetary Sciences OR Environmental Sciences\end{tabular}} &

\begin{tabular}{p{\linewidth}}Journals OR Conference Proceedings\end{tabular}& 2013 & 5684 & 60 \\

%\setlength{\extrarowheight}{25pt}

\begin{tabular}{p{\linewidth}}Life \& Earth 2019\end{tabular} & & & 2018 & 5734 & 60 \\

{\renewcommand{\arraystretch}{4.5}%

&&&& \\

}

\hline

%\setlength{\extrarowheight}{20pt} \hline

\end{tabular}

}

\end{center}

\endgroup

\end{table}

(ii) Retrieving articles

Next, we retrieved articles by sending a query from the Scopus search page(scopus.com/form.uri?display=advanced). Table\ref{tbl4-3} shows the summary of queries to retrieve the article data. Each query consists of the Scopus sub-subject, publication period, and ISSN(International Standard Serial Number). Scopus sub-subject is identical to the subject area of the corresponding source set. We set the publication period as from January to June of the target year. For ISSN, we connected all ISSNs in the source set with "OR". We excluded sources without specified ISSN by Scopus from the query.

\begin{table}[htbp]

\renewcommand{\tabcolsep}{3pt}

\begingroup

\renewcommand{\arraystretch}{1.1}

\caption{Summary of Query for Article Data}

\label{tbl4-3}

\begin{center}

\scalebox{1.0}[1.0] {

\begin{tabular}{p{0.27\linewidth}p{0.54\linewidth}p{0.1\linewidth}<{\raggedleft}p{0.1\linewidth}<{\raggedleft}}

\thickhline

\begin{tabular}{p{\linewidth}}Dataset\end{tabular} & \begin{tabular}{p{\linewidth}}Query\end{tabular} & \begin{tabular}{p{\linewidth}}\# of valid sources\end{tabular} & \begin{tabular}{p{\linewidth}}\# of articles\end{tabular} \\ \thickhline

\begin{tabular}{p{\linewidth}}Math \& Computer 2014\end{tabular} & \begin{tabular}{p{\linewidth}}SUBAREA(MATH OR COMP) AND PUBDATETXT(January 2014 OR … OR June 2014) AND ISSN(...)\end{tabular} & 133 & 9336 \\ \hline

\begin{tabular}{p{\linewidth}}Math \& Computer 2019\end{tabular} & \begin{tabular}{p{\linewidth}}SUBAREA(MATH OR COMP) AND PUBDATETXT(January 2019 OR … OR June 2019) AND ISSN(...)\end{tabular} & 133 & 14330 \\ \hline

\begin{tabular}{p{\linewidth}}Life \& Earth 2014\end{tabular} & \begin{tabular}{p{\linewidth}}SUBJAREA(AGRI OR EART OR ENVI) AND PUBDATETXT(January 2014 OR … OR June 2014) AND ISSN(...)\end{tabular} & 52 & 7717 \\ \hline

\begin{tabular}{p{\linewidth}}Life \& Earth 2019\end{tabular} & \begin{tabular}{p{\linewidth}}SUBJAREA(AGRI OR EART OR ENVI) AND PUBDATETXT(January 2019 OR … OR June 2019) AND ISSN(...)\end{tabular} & 53 & 7735 \\ \thickhline

\end{tabular}

}

\end{center}

\endgroup

\end{table}

(iii) Retrieving AAS of articles

To obtain AAS of the articles, we directly examined AAS of each article using the Altmetric Bookmarklet, a free tool released by Altmetric.com. Altmetric Bookmarklet on a specific webpage of the target article tries to detect the article's DOI and displays AAS by querying the AAS database server using the found DOI as a key. We excluded articles without AAS from any analysis regarding AAS.

\subsubsection{Video Dataset}

Next, we describe the datasets of YouTube videos that mention the articles obtained in \ref{article-dataset}. Table\ref{tbl4-4} shows the overview of the video dataset. To obtain video data, we (i) collect article-mentioning video candidates by sending queries using the Google API, (ii) select the videos that correctly mention the article among the candidate videos, and (iii) assign labels of the purpose of article-mention to the selected videos.

\begin{table}[htbp]

\renewcommand{\tabcolsep}{3pt}

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\renewcommand{\arraystretch}{1.1}

\caption{Overview of Video Dataset}

\label{tbl4-4}

\begin{center}

\scalebox{1.0}[1.0] {

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\hline

\begin{tabular}{p{\linewidth}}Dataset\end{tabular} & \begin{tabular}{p{\linewidth}}\# of total videos\end{tabular} & \begin{tabular}{p{\linewidth}}\# of sampled videos\end{tabular} & \begin{tabular}{p{\linewidth}}\# of articles mentioned by samples\end{tabular} & \begin{tabular}{p{\linewidth}}\# of cited articles(\%)\end{tabular} & \begin{tabular}{p{\linewidth}}\# of articles with AAS(\%)\end{tabular} \\ \hline

\begin{tabular}{p{\linewidth}}Math \& Computer 2014\end{tabular} & 143 & 100 & 77 & 75(97.4) & 47(61.0) \\

\begin{tabular}{p{\linewidth}}Math \& Computer 2019\end{tabular} & 79 & 79 & 64 & 62(96.9) & 37(57.8) \\

\begin{tabular}{p{\linewidth}}Life \& Earth 2014\end{tabular} & 112 & 100 & 71 & 71(100) & 67(94.4) \\

\begin{tabular}{p{\linewidth}}Life \& Earth 2019\end{tabular} & 284 & 100 & 59 & 58(98.3) & 58(98.3) \\ \hline

\end{tabular}

}

\end{center}

\endgroup

\end{table}

\paragraph{Collecting article-mentioning video candidates}

\label{sec4-1-3-2-1}

To collect video candidates, we used Google Youtube Data V3 provided by Google. First, for each paper, we queried video IDs twice, with each article's DOI and the URL redirected by the DOI system as the key, respectively. Using each unique video ID in the queried set, we queried video data, yielding sets of article-mentioning video candidates. We collected the video candidates from 24 July, 2020 to 21 August, 2020.

\paragraph{Selecting article-mentioning videos}

Among video candidates, we selected only the videos that correctly mention the DOI or the redirected URL. Specifically, we first lowercased each video's title and description and removed whitespace, tab(\textbackslash t) and newline(\textbackslash n) from them. Next, only the videos containing a string that matches the DOI or the URL are accepted as the article-mentioning videos, yielding the video dataset populations. Finally, we randomly sampled videos from each population, yielding the video datasets to be analyzed in this experiment. We selected 100 if the population has over 100 videos; otherwise, all videos in the population.

\paragraph{Labeling the purpose of article-mention}

Lastly, we assigned labels to the videos according to the proposed taxonomy regarding article-mention purposes. We manually examined each video and its metadata and determined the label according to the criteria on table\ref{tbl3-2}.

\section{Results}

We present the results of experiments using the article and video datasets described above.

\subsection{Validation of Article-mentioning Video's Impact on Citation Count and AAS}

We present a statistical analysis on the citation counts and AAS distributions of the articles with and without videos in each dataset. We set $m$ to 2, matching two articles without videos to each article with video, and the significance level $\alpha$ in both Normaltest and t-test to 0.05.

\subsubsection{Impact on Citation Count}

For Math \& Computer 2014/2019 and Life \& Earth 2014/2019 respectively, Figure\ref{fig4-1t} and Figure\ref{fig4-2t} show the distributions of citation counts for the articles, and Table\ref{tbl4-1t} and Table\ref{tbl4-2t} show the mean of each distribution and P-values of Normaltest and t-test. In each dataset, the P-values of Normaltest are greater than $\alpha$ in all distributions, suggesting that each distribution is normal. The mean of logarithmic citation counts is higher in the articles with videos than in the articles without videos, and each t-test's P-value was smaller than $\alpha$, indicating that both distributions originated from different populations. The results concluded that the article-mentioning videos on YouTube significantly contribute to increasing the articles' citation count in both academic fields in 2014 and 2019.

\begin{minipage}{\linewidth}

\begin{center}

\includegraphics[width=11cm]{pics/fig4-1t.png}

\captionof{figure}{Citation count distributions in Math \& Computer}

\label{fig4-1t}

\captionof{table}{Statistical analysis on citation counts in Math \& Computer}

\begin{tabular}{rrrrr}

\hline

\multicolumn{1}{l}{} & \multicolumn{2}{r}{Math \& Computer 2019} & \multicolumn{2}{r}{Math \& Computer 2014} \\

\multicolumn{1}{l}{} & Without videos & With videos & Without videos & With videos \\ \hline

Mean & 0.62 & 0.78 & 1.30 & 1.56 \\

P(Normaltest) & 0.448 & 0.872 & 0.835 & 0.162 \\

P(t-test) & \multicolumn{2}{r}{0.018} & \multicolumn{2}{r}{0.001} \\ \hline

\end{tabular}

\label{tbl4-1t}

\includegraphics[width=11cm]{pics/fig4-2t.png}

\captionof{figure}{Citation count distributions in Life \& Earth}

\label{fig4-2t}

\captionof{table}{Statistical analysis on citation counts in Life \& Earth}

\begin{tabular}{rrrrr}

\hline

\multicolumn{1}{l}{} & \multicolumn{2}{r}{Life \& Earth 2019} & \multicolumn{2}{r}{Life \& Earth 2014} \\

\multicolumn{1}{l}{} & Without videos & With videos & Without videos & With videos \\ \hline

Mean & 0.75 & 1.15 & 1.54 & 1.85 \\

P(Normaltest) & 0.529 & 0.547 & 0.862 & 0.992 \\

P(t-test) & \multicolumn{2}{r}{0.000} & \multicolumn{2}{r}{0.000} \\ \hline

\end{tabular}

\label{tbl4-2t}

\end{center}

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\subsubsection{Impact on AAS}

Like the analysis above, for Math \& Computer 2014/2019 and Life \& Earth 2014/2019 respectively, Figure\ref{fig4-3t} and Figure\ref{fig4-4t} show the distributions of AAS for the articles, and Table\ref{tbl4-3t} and Table\ref{tbl4-4t} show the mean of each distribution and P-values of Normaltest and t-test. In all datasets except for Life \& Earth 2014, the P-values of Normaltest exceed $\alpha$, suggesting that each distribution is normal. This result makes the t-test for Life \& Earth 2014 questionable, but we found significant differences between the two distributions in the dataset in Figure\ref{4-4t}, concluding that their populations are reasonably different. The mean of logarithmic AAS is higher in the articles with videos than in the articles without videos, and each t-test's P-value is less than $\alpha$, indicating that both distributions originate from different populations. The results concluded that the article-mentioning videos on YouTube significantly contribute to increasing the articles' AAS in both academic fields in 2014 and 2019.

\begin{minipage}{\linewidth}

\begin{center}

\includegraphics[width=11cm]{pics/fig4-3t.png}

\captionof{figure}{AAS distributions in Math \& Computer}

\label{fig4-3t}

\captionof{table}{Statistical analysis on AAS in Math \& Computer}

\begin{tabular}{rrrrr}

\hline

\multicolumn{1}{l}{} & \multicolumn{2}{r}{Math \& Computer 2019} & \multicolumn{2}{r}{Math \& Computer 2014} \\

\multicolumn{1}{l}{} & Without videos & With videos & Without videos & With videos \\ \hline

Mean & 0.51 & 0.91 & 0.39 & 0.92 \\

P(Normaltest) & 0.114 & 0.191 & 0.117 & 0.073 \\

P(t-test) & \multicolumn{2}{r}{0.004} & \multicolumn{2}{r}{0.000} \\ \hline

\end{tabular}

\label{tbl4-3t}

\includegraphics[width=11cm]{pics/fig4-4t.png}

\captionof{figure}{AAS distributions in Life \& Earth}

\label{fig4-4t}

\captionof{table}{Statistical analysis on AAS in Life \& Earth}

\begin{tabular}{rrrrr}

\hline

\multicolumn{1}{l}{} & \multicolumn{2}{r}{Life \& Earth 2019} & \multicolumn{2}{r}{Life \& Earth 2014} \\

\multicolumn{1}{l}{} & Without videos & With videos & Without videos & With videos \\ \hline

Mean & 1.36 & 2.46 & 0.84 & 1.88 \\

P(Normaltest) & 0.494 & 0.075 & \textbf{0.004} & \textbf{0.041} \\

P(t-test) & \multicolumn{2}{r}{0.000} & \multicolumn{2}{r}{0.000} \\ \hline

\end{tabular}

\label{tbl4-4t}

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\subsection{Comparison of Citation Count and AAS Distributions by Article-mention Purpose}

Next, we split each video dataset by the article-mention purpose, organize the article groups mentioned by each video group, and quantitatively compare the citation count and AAS distributions in each article group. We set the significance level $\alpha$ of Normaltest to 0.05.

\subsubsection{Comparison of Citation Count}

First, for Math \& Computer 2014 and 2019, Figure\ref{fig4-5t} shows each distribution of the citation counts, and Table\ref{tbl4-5t} shows the sample sizes and the means of distributions. As shown in Table\ref{tbl4-5t}, the mean citation count is relatively high for the Explanation group compared to the other article groups. In 2019, the mean and median values in the Explanation group and the Reference group were almost identical, and there is no significant difference between them. The results conclude that, in both years, the videos for explaining the articles have the most predominant impact on the citation counts.

Next, for Life \& Earth 2014 and 2019, Figure\ref{fig4-6t} shows each distribution of the citation counts, and Table\ref{tbl4-6t} shows the sample sizes and the means of distributions. Table\ref{tbl4-6t} shows that the mean citation count is highest for the Explanation group, similar to the results for Math \& Computer. The results conclude that, in both years, the videos for explaining the articles have the most significant impact on the citation counts.

\begin{minipage}{\linewidth}

\begin{center}

\includegraphics[width=12cm]{pics/fig4-5t.png}

\captionof{figure}{Citation count distributions by video purposes in Math \& Computer}

\label{fig4-5t}

\captionof{table}{Statistics on citation counts by video purposes in Math \& Computer}

\begin{tabular}{rrrrrrrrr}

\hline

& \multicolumn{4}{r}{Math \& Computer 2019} & \multicolumn{4}{r}{Math \& Computer 2014} \\ \hline

Video purpose & Exp & News & Sup & Ref & Exp & News & Sup & Ref \\

\# of articles & 16 & 8 & 25 & 15 & 10 & - & 16 & 52 \\

Mean & 0.97 & 0.67 & 0.58 & 0.98 & 1.83 & - & 1.47 & 1.57 \\

\hline

\end{tabular}

\label{tbl4-5t}

\includegraphics[width=12cm]{pics/fig4-6t.png}

\captionof{figure}{Citation count distributions by video purposes in Life \& Earth}

\label{fig4-6t}

\captionof{table}{Statistics on citation counts by video purposes in Life \& Earth}

\begin{tabular}{rrrrrrrrr}

\hline

& \multicolumn{4}{r}{Life \& Earth 2019} & \multicolumn{4}{r}{Life \& Earth 2014} \\ \hline

Video purpose & Exp & News & Sup & Ref & Exp & News & Sup & Ref \\

\# of articles & 6 & 31 & 3 & 29 & 5 & 13 & 5 & 53 \\

Mean & 1.65 & 1.12 & 1.02 & 1.23 & 2.01 & 1.59 & 1.77 & 1.86 \\

\hline

\end{tabular}

\label{tbl4-6t}

\end{center}

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\subsubsection{Comparison of AAS}

As in the citation count analysis, for Math \& Computer 2014 and 2019, Figure\ref{fig4-7t} shows each distribution of AAS, and Table\ref{tbl4-7t} shows the sample sizes and the means of distributions. Table\ref{tbl4-7t} shows that the mean AAS is highest for the Reference group. The results imply that, in both years, the videos referencing articles have the most eminent impact on the AAS.

Next, for Life \& Earth 2014 and 2019, Figure\ref{fig4-8t} shows each distribution of AAS, and Table\ref{tbl4-8t} shows the sample sizes and the means of distributions. Figure\ref{fig4-8t} and Table\ref{tbl4-8t} show that, in 2019, the mean and median AAS in the Explanation group are the greatest, suggesting that the videos for explaining articles have the most predominant impact on AAS. On the other hand, in 2014, the mean and medians AAS in the News group are the largest, indicating that the videos for article dissemination are the most influential. For the Reference group, the mean and median AAS are the second greatest in both years, implying that the impact of videos referencing articles is relatively significant on AAS.

\begin{minipage}{\linewidth}

\begin{center}

\includegraphics[width=12cm]{pics/fig4-7t.png}

\captionof{figure}{AAS distributions by video purposes in Math \& Computer}

\label{fig4-7t}

\captionof{table}{Statistics on AAS by video purposes in Math \& Computer}

\begin{tabular}{rrrrrrrrr}

\hline

& \multicolumn{4}{r}{Math \& Computer 2019} & \multicolumn{4}{r}{Math \& Computer 2014} \\ \hline

Video purpose & Exp & News & Sup & Ref & Exp & News & Sup & Ref \\

\# of articles & 12 & 5 & 12 & 10 & 9 & - & 13 & 28 \\

Mean & 0.93 & 1.12 & 0.20 & 1.54 & 0.89 & - & 0.48 & 1.08 \\

\hline

\end{tabular}

\label{tbl4-7t}

\includegraphics[width=12cm]{pics/fig4-8t.png}

\captionof{figure}{AAS distributions by video purposes in Life \& Earth}

\label{fig4-8t}

\captionof{table}{Statistics on AAS by video purposes in Life \& Earth}

\begin{tabular}{rrrrrrrrr}

\hline

& \multicolumn{4}{r}{Life \& Earth 2019} & \multicolumn{4}{r}{Life \& Earth 2014} \\ \hline

Video purpose & Exp & News & Sup & Ref & Exp & News & Sup & Ref \\

\# of articles & 6 & 31 & 3 & 29 & 4 & 13 & 4 & 50 \\

Mean & 2.73 & 2.54 & 1.86 & 2.61 & 1.23 & 2.28 & 1.33 & 1.92 \\

\hline

\end{tabular}

\label{tbl4-8t}

\end{center}

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\subsection{Predicting Future Citation Count using YouTube Score}

Finally, we evaluate the predictability of future citation count by the YouTube scores of post-period article datasets and identify the video methods with which prediction is effective. First, we assign the YouTube score to each article and then determine whether the YouTube scores and the citation counts had been growing or saturated between the pre-period and the post-period. For the KStest for testing the goodness of fit, we set the significance level $\alpha$ to 0.05. Next, for the pre-period datasets, we perform regression analysis between the YouTube score and the citation count in each article group split by the video's purpose of article-mention and assess the predictability of future citation count using the YouTube score of the article in the early stage of publication. We estimate the article group that shows a significant correlation coefficient as a video method with effective prediction.

\subsubsection{Saturation Test for YouTube Score and Citation Count}

First, for Math \& Computer and Life \& Earth, Figure\ref{fig4-9t} and Figure\ref{fig4-10t} show the distributions of the YouTube scores and the citation counts of the articles with videos, and Table\ref{tbl4-9t} and Table\ref{tbl4-10t} shows the means of the distributions and the P-values of KStest, respectively. In each academic field, the P-value of KStest exceeds $\alpha$, indicating a good fit between two years' YouTube scores. Table\ref{tbl4-9t} shows a considerable disparity between the mean YouTube scores, which may be due to the outliers in Math \& Computer 2014. On the other hand, there is a difference in the citation count distributions between two years, and KStest does not provide a good fit. Based on the results above, we conclude that the YouTube score is saturated, and the citation count is growing for the articles with videos in Math \& Computer 2019 and Life \& Earth 2019.

\begin{minipage}{\linewidth}

\begin{center}

\includegraphics[width=12cm]{pics/fig4-9t.png}

\captionof{figure}{Distribution of YouTube scores and citation counts in Math \& Computer}

\label{fig4-9t}

\captionof{table}{Mean YouTube score and citation count and KStest in Math \& Computer}

\begin{tabular}{rrrrr}

\hline

& \multicolumn{2}{r}{YTscore} & \multicolumn{2}{r}{Citation count} \\

& 2019 & 2014 & 2019 & 2014 \\ \hline

Mean & 1.99 & 2.40 & 0.78 & 1.56 \\

P(KStest) & \multicolumn{2}{r}{\textbf{0.149}} & \multicolumn{2}{r}{0.000} \\ \hline

\end{tabular}

\label{tbl4-9t}

\includegraphics[width=12cm]{pics/fig4-10t.png}

\captionof{figure}{Distribution of YouTube scores and citation counts in Life \& Earth}

\label{fig4-10t}

\captionof{table}{Mean YouTube score and citation count and KStest in Life \& Earth}

\begin{tabular}{rrrrr}

\hline

& \multicolumn{2}{r}{YTscore} & \multicolumn{2}{r}{Citation count} \\

& 2019 & 2014 & 2019 & 2014 \\ \hline

Mean & 3.33 & 3.57 & 1.06 & 1.84 \\

P(KStest) & \multicolumn{2}{r}{\textbf{0.684}} & \multicolumn{2}{r}{0.000} \\ \hline

\end{tabular}

\label{tbl4-10t}

\end{center}

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\subsubsection{Regression Analysis of YouTube Scores and Citation Counts in Articles Split by Video Method}

Next, Figure\ref{fig4-11t} and Figure\ref{fig4-12t} show a scatter plot of the YouTube scores and the citation counts, and Table\ref{tbl4-11t} and Table\ref{tbl4-12t} show the results of the regression analysis performed on each article group split by the video's purpose of article-mention in Math \& Computer 2014 and Life \& Earth 2014, respectively.

For Math \& Computer 2014, Table\ref{tbl4-11t} shows that the Explanation group shows the highest correlation of 0.54, although the number of samples is only 6(8.5\%), and the significant variance from the regression line is visible in Figure\ref{fig4-11t}, which implies a lack of reliability. On the other hand, the second-highest correlation was present in the Supplementary group with a coefficient of 0.37 and samples of 16(22.5\%). Also, Figure\ref{fig4-11t} shows the suppressed variance from the regression line compared to the case of the Explanation group. The results concluded that supplementary video on YouTube could effectively predict the future citation count of the articles in the early stage of publication in mathematics and computer science.

Next, for the Life \& Earth 2014, Table\ref{tbl4-12t} shows that the Supplementary group shows the highest correlation of 0.51, but the number of samples is only 3, lacking significance. On the other hand, the Reference group is the next highest correlated, showing a weak correlation of 0.15, and the considerable variance from the regression line is visible in Figure \ref{fig4-11t}, proposing that the YouTube score is not a sufficient predictive measure. The results suggest that we could not extract video methods that effectively predict an article's future citation count in the early stage of publication in life and earth sciences.

\begin{minipage}{\linewidth}

\begin{center}

\includegraphics[width=10.5cm]{pics/fig4-11t.png}

\captionof{figure}{Scatter plot of YouTube scores and citation counts for Math \& Computer 2014}

\label{fig4-11t}

\captionof{table}{Regression analysis of YouTube scores and citation counts for Math \& Computer 2014}

\begin{tabular}{rrrrr}

\hline

Purpose & \# of articles(\%) & Correlation coefficient & Slope & Y section \\ \hline

News & - & - & - & - \\

Exp & 6(8.5) & \textbf{0.54} & 0.70 & 0.36 \\

Ref & 49(69.0) & 0.11 & 0.05 & 1.44 \\

Sup & 16(22.5) & \textbf{0.37} & 0.21 & 0.85 \\ \hline

Total & 71(100) & 0.13 & 0.07 & 1.39 \\ \hline

\end{tabular}

\label{tbl4-11t}

\includegraphics[width=10.5cm]{pics/fig4-12t.png}

\captionof{figure}{Scatter plot of YouTube scores and citation counts for Life \& Earth 2014}

\label{fig4-12t}

\captionof{table}{Regression analysis of YouTube scores and citation counts for Life \ & Earth 2014}

\begin{tabular}{rrrrr}

\hline

Purpose & \# of articles(\%) & Correlation coefficient & Slope & Y section \\ \hline

News & 10(14.9) & -0.32 & -0.17 & 2.21 \\

Exp & 4(6.0) & -0.04 & -0.01 & 2.04 \\

Ref & 50(74.6) & 0.15 & 0.04 & 1.71 \\

Sup & 3(4.5) & \textbf{0.51} & 0.51 & 0.44 \\ \hline

Total & 71(100) & 0.13 & 0.07 & 1.39 \\ \hline

\end{tabular}

\label{tbl4-12t}

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\chapter{Discussion}

\label{chap05}

\section{Trends of Article-mentioning YouTube Videos}

In this experiment, we obtained datasets of the articles in two broad research fields and YouTube videos mentioning them. There has not been any study that analyzes article-mentioning videos using a large amount of academic literature data such as that obtained in this experiment. Therefore, we conduct a statistical analysis of the datasets and discuss science communication trends through YouTube videos mentioning articles.

\subsection{Activity of Video Production}

We evaluate the efforts to publish the article-mentioning videos in the pre-period and post-period, comparing the activity levels. In each video dataset, we focus on the videos whose release date is within one year from the publication of the mentioned article (hereafter "early videos") and evaluate the activity level of article-mentioning YouTube videos based on the number of early videos, the number of articles with early videos, and the percentage of the total. For selecting early videos, we virtually set the publication date of articles to be the first day of the publication month and considered a video as an early video if the time difference between the video release date and the article publication date does not exceed 365 days.

\begin{table}[htbp]

\begingroup

\renewcommand{\arraystretch}{1.1}

\caption{Statistics on the early videos}

\label{tbl5-2t}

\begin{center}

\scalebox{1.0}[1.0] {

\begin{tabular}{rrrrr}

\hline

& \multicolumn{2}{r}{Math \& Computer} & \multicolumn{2}{r}{Life \& Earth} \\

& 2014 & 2019 & 2014 & 2019 \\ \hline

\# of early videos & 79 & 63 & 32 & 261 \\

\begin{tabular}[c]{@{}r@{}}\# of articles with early videos/\# of total articles\\ (\%)\end{tabular} & \begin{tabular}[c]{@{}r@{}}67/9336\\ (0.72)\end{tabular} & \begin{tabular}[c]{@{}r@{}}50/14330\\ (0.35)\end{tabular} & \begin{tabular}[c]{@{}r@{}}21/7717\\ (0.27)\end{tabular} & \begin{tabular}[c]{@{}r@{}}124/7735\\ (1.60)\end{tabular} \\

\begin{tabular}[c]{@{}r@{}}\# of sources holding articles with early videos/\# of total sources\\ (\%)\end{tabular} & \begin{tabular}[c]{@{}r@{}}25/133\\ (18.8)\end{tabular} & \begin{tabular}[c]{@{}r@{}}26/133\\ (19.5)\end{tabular} & \begin{tabular}[c]{@{}r@{}}12/52\\ (23.1)\end{tabular} & \begin{tabular}[c]{@{}r@{}}24/53\\ (45.3)\end{tabular} \\

\begin{tabular}[c]{@{}r@{}}\# of sub-subjects holding articles with early videos/\# of total sub-subjects\\ (\%)\end{tabular} & \begin{tabular}[c]{@{}r@{}}18/43\\ (41.9)\end{tabular} & \begin{tabular}[c]{@{}r@{}}20/46\\ (43.5)\end{tabular} & \begin{tabular}[c]{@{}r@{}}9/25\\ (36.0)\end{tabular} & \begin{tabular}[c]{@{}r@{}}19/32\\ (59.4)\end{tabular} \\ \hline

\end{tabular}

}

\end{center}

\endgroup

\end{table}

Table\ref{tbl5-2t} shows the statistics for the early videos and articles with them. First, we show the number of articles with early videos and their percentage for each article dataset. Next, for each publication source in each article dataset, the number of sources that hold any article with early videos and their percentage is revealed. Finally, for each sub-subject given to each source by Scopus, the number of sub-subjects that hold any article with early videos and their percentage is presented. In Math \& Computer, we noted a slight decrease in the number of early videos between two years, from 79 to 63. However, considering that article-mentioning YouTube videos have not yet been a mainstream science communication method, we do not recognize a significant change in the activity level in producing article-mentioning videos in this field between the two years. Also, the percentage of sources and sub-subjects of two years are very similar, so we can conclude that the activity level of article-mentioning YouTube videos in mathematics and computer science is similar between 2014 and 2019.

On the other hand, for Life \& Earth, the articles in 2019 hold 261 early videos compared to 32 early videos for those in 2014, which is 8.2 times more. Furthermore, the number of articles and sources with early videos in 2019 is about 6 and 2 times as large as in 2014, respectively. The results imply that there had been an explosive increase in producing article-mentioning YouTube videos in 2019 compared to in 2014 in life and earth sciences. By watching the videos, we confirmed that the leading cause of the increased interest is the successful event of observing the black hole in 2019. Six reports on the event(DOI: 10.3847/2041-8213/ab0ec7, 10.3847/2041-8213/ab0c96, 10.3847/2041-8213/ab0c57, 10.3847/2041-8213/ab0e85, 10.3847/ 2041-8213/ab0f43, 10.3847/2041-8213/ab1141) received remarkable attention, accounting for 93(26.5\%) of the 351 article mentions in Life\& Earth 2019. The videos mainly aimed to summarize the content of the reports or to disseminate it. We believe that this analysis confirms the case where a significant scientific event with a high affinity to the video has a strong impact on the activity level of scientific communication on YouTube.

\subsection{Video Production Bias to Citation Rate of Article Sources}

There is insufficient knowledge from previous studies on what kind of articles tend to produce article-mentioning videos. This section discusses the bias of article-mentioning videos in both fields to be unevenly distributed concerning the articles' quality. Figure\ref{fig5-3t} shows the number of videos mentioning the articles from each publication source in both pre-period datasets, sorted by the descending source's CiteScore. Table \ref{tbl5-4t} shows the number of articles with videos and sources holding them in the top 50\% and bottom 50\% of the CiteScore sources, revealing the former higher than the latter in both fields. In particular, the gap between the two source groups is more prominent in Math \& Computer than in Life \& Earth. The results conclude that the article-mentioning videos are unevenly distributed concerning the citation rate of article source, suggesting that scientific communication videos prefer even higher-ranking sources, even among prominent journals and conference proceedings in a particular field. Also, we confirmed the cases where the bias level of video production concerning the citation rate differed depending on the research field.

\begin{table}[htbp]

\begingroup

\renewcommand{\arraystretch}{1.1}

\caption{Number of articles and sources with videos in top/bottom CiteScore group}

\label{tbl5-4t}

\begin{center}

\scalebox{1.0}[1.0] {

\begin{tabular}{rrrr}

\hline

Dataset & Source CiteScore & \# of articles with videos & \# of sources with videos \\ \hline

\multirow{2}{\*}{Math \& Computer 2014} & Top 50％ & 48 & 19 \\

& Bottom 50％ & 29 & 11 \\

\multirow{2}{\*}{Life \& Earth 2014} & Top 50％ & 41 & 15 \\

& Bottom 50％ & 30 & 11 \\ \hline

\end{tabular}

}

\end{center}

\endgroup

\end{table}

\begin{minipage}{\textwidth}

\captionof{figure}{Source CiteScore and number of articles with videos}

\label{fig5-3t}

\begin{minipage}{\textwidth}

\centering

\includegraphics[width=16cm]{pics/fig5-3t-a.png}

\captionof{subfigure}{Math \& Computer 2014}

\label{fig5-3t-a}

\end{minipage}

\begin{minipage}{\textwidth}

\centering

\includegraphics[width=16cm]{pics/fig5-3t-b.png}

\captionof{subfigure}{Life \& Earth 2014}

\label{fig5-3t-b}

\end{minipage}

\end{minipage}

\section{Differences in Video's Impact in Different Research Fields}

We already observed that the mean citation count and AAS of the articles with videos were higher than those without videos consistently for the two research fields and two publication periods in the experiment. To discuss how the article-mentioning video's impact on the citation count and AAS varies by research field, we calculate $Δ\mu$, the difference between the mean values $\mu$ of the articles with videos and without videos for the article dataset of the research field $A$ in a specific publication period, as shown in Equation\ref{eq5-1}. Note that $Δ\mu$ is the logarithm of the ratio of the target value's geometric mean of the articles with videos to those without videos.

\begin{equation}

\centering

\label{eq5-1}

Δ\mu(A) = \mu \_{with videos}(A) - \mu \_{without videos}(A)

\end{equation}

Next, let $r(A, B)$ obtained by Equation\ref{eq5-2} be the index representing the magnification of the video's impact in field B relative to field A on the articles of the same publication period. Note that $r(A, B)$ is the ratio of field B to field A for the ratio of the target value's geometric mean for the articles with and without video.

\begin{equation}

\centering

\label{eq5-2}

r(A,B) = 10 ^{(Δ\mu(B) - Δ\mu(A))}

\end{equation}

\begin{table}[htbp]

\begingroup

\renewcommand{\arraystretch}{1.1}

\caption{$Δ\mu$ and $r$ for each article index}

\label{tbl5-1t}

\begin{center}

\scalebox{1.0}[1.0] {

% Please add the following required packages to your document preamble:

% \usepackage{multirow}

\begin{tabular}{rrrrr}

\thickhline

\multirow{2}{\*}{Article index} & \multirow{2}{\*}{Period} & \multicolumn{2}{c}{$Δ\mu$} & \multirow{2}{\*}{$r(COMP, LIFE)$} \\

& & $COMP$ & $LIFE$ & \\ \thickhline

\multirow{2}{\*}{Citation count} & 2014 & 0.16 & 0.40 & 1.74 \\

& 2019 & 0.26 & 0.31 & 1.12 \\ \hline

\multirow{2}{\*}{AAS} & 2014 & 0.40 & 1.10 & 5.01 \\

& 2019 & 0.53 & 1.04 & 3.24 \\ \thickhline

\end{tabular}

}

\end{center}

\endgroup

\end{table}

Table\ref{tbl5-1t} shows $Δ\mu$ and $r$ values calculated for each article dataset. Regarding citation count, $Δ\mu$ is larger in Life \& Earth (Hereafter $LIFE$) than in Math \& Computer (Hereafter $COMP$) in each dataset. In particular, for the articles in the first half of 2014, $r(COMP, LIFE)$ reached 1.74, confirming the significant difference between the two research fields in the video's impact on the citation count. As for AAS, $Δ\mu$ is greater for $LIFE$ than for $COMP$. Regarding $r(COMP, LIFE)$, the video's impact on Life \& Earth outperformed that on Math \& Computer with 5.01 in the first half of 2014 and with 3.24 in the first half of 2019.

The results imply the differences between the two research fields in the article-mentioning video's impact on the article's citation count and AAS, the latter more extensive than the former. The conclusions are consistent with the assertions\cite{58,59} that the overall approach to science communication varies by academic field.

\section{Predicting Citation Count using Video's Popularity}

In the proposed method, we first confirmed the saturation of the YouTube score of the post-period dataset and then assessed the predictability of the future citation count based on the correlation between the YouTube score and the citation counts in the pre-period. This section discusses the experimental results and the notable points when using this method.

\subsection{Growth and Saturation of Article Index}

Our experiments verified that the YouTube score saturates and the citation count grows about 1-1.5 years after publication for the articles in both research fields. This result is consistent with the reports\cite{43,52} that the increase rate in Altmetrics is higher than the citation rate in the early stage of publication, and the saturation of citation count tends to lag behind Altmetrics, supporting the assumption in the proposed method that YouTube has similar properties to social media as a science communication platform.

However, we must be cautious about the assumptions of the population growth model of the article index. The two distributions to be compared are data from different article sets, and the post-period distribution could be "saturated" even if the test verifies "growing". It is acknowledgeable that it needs further time for the citation count to saturate for 1.5-year-old articles, and it is reasonable to reconsider the test results in the case of saturation. On the other hand, for the YouTube score, findings on the saturation of the academic video's view count are scarce. Considering that the article-mentioning video is still an emerging science communication method, it is reasonable to assume that the view count's saturation period would appear earlier than that of general popular videos. Although the experiment showed that the post-period YouTube scores are saturated, we must note the possible failure mentioned above in using this method.

\subsection{Predicting Citation Count with YouTube Score}

This section describes the cautions and expected improvements in predicting the citation count by the YouTube score for articles in the early stage of publication. First of all, we expect the prediction accuracy to vary depending on the field. The regression analysis conducted on Math \& Computer 2014 found the videos for explaining and supplementing the article to be valid predictor, showing a significant correlation in the Explanation and Supplementary groups. In contrast, the analysis revealed no valid video method for prediction in Life \& Earth 2014. However, considering that the sample size of the Explanation and Supplementary groups in Life \& Earth 2014 was only 4 and 3, respectively, allowing no significant analysis, we expect larger datasets of articles and videos for a valid comparison between the two fields.

Regarding the taxonomy of the video method proposed in this method, we find limitations in the classification of the purpose of article-mention. The experimental result empirically suggests the need for further subdivision of each category to improve prediction accuracy. In particular, the articles labelled with Reference accounted for the most significant percentage of articles in Math \& Computer 2014 and Life \& Earth 2014(69\% and 75\%, respectively), but we observed no significant correlation from the regression analysis for them. To improve the method, we can devise a new classification method that considers the other properties of the article-mentioning video. For instance, the classification method for Twitter accounts\cite{53} could provide hints for the classification of YouTube channels that publishes the article-mentioning videos.

Finally, we find limitations of the YouTube score as a measure of popularity on YouTube and expect improvements. First, with the current YouTube score, the prediction model cannot handle articles with multiple videos with different purposes of article-mention. The number of such articles in Math \& Computer 2014 Life \& Earth 2014 was relatively small, 6(7.8\%) and 4(5.6\%), respectively. However, this percentage could increase as efforts to promote article-mentioning videos become more active in the future. Therefore, it is necessary to design a new score and prediction model covering such articles for our method's robustness. For example, we can establish a weight $c\_{j}$ for each video label $j$ as in Equation\ref{eq5-3}, and propose a score obtained by summing the weighted view counts for the video $i$ labelled with $j$.

\begin{equation}

\centering

\label{eq5-3}

\log \_{10} \sum \_{j} c \_{j} \Big\{ \sum \_{i} (viewcount) \_{ij} \Big\}

\end{equation}

Equation\ref{eq5-3} can extend the target of the regression analysis from the article groups split by video labels to the entire articles in a dataset, and by calculating the weights that best fit any given policy, we can expect the model to be robust to labels.

On the other hand, considering that it is the academia that mainly influences an article's citation, it is essential to extract the video's popularity within the academic community to improve the accuracy of predicting the citation count. Given that videos are more effective than text in explaining and demonstrating research\cite{7}, the academic video's primary purpose of article-mention viewed by academics is to explain or supplement research content, and such videos may strongly reflect the article's popularity among the academic community. Therefore, in predicting the future citation count using the video's popularity, it is reasonable to revise the YouTube score considering the video's purpose of article-mention.

\chapter{Conclusion}

\label{chap06}

\section{Conclusion of Study}

The purpose of this study was to verify the effectiveness of the impact of article-mentioning videos on YouTube on the citation count and Altmetrics, to identify effective video methods, and to evaluate the predictability of future citation count using video's popularity, thereby contributing to the efficiency of allocating resources and developing research strategies. This section presents the conclusions of this study.

We proposed a method for (i)validating the impact of article-mentioning YouTube videos on the citation count and AAS by comparing the homogeneous articles with and without videos, (ii)clarifying the difference in the video's impact depending on the article-mention purpose, and (iii)predicting the future citation count of an article in the early stage of publication using the video's popularity, using large-scale academic literature and video data.

Experiments using four datasets from two research fields and two publication periods validated that the article-mentioning videos contributed to the citation count and AAS, revealing a more substantial impact in life and earth sciences than in mathematics and computer science, regardless of the publication period.

Regarding the difference in the video's impact by article-mention purpose, the video explaining the article was the most influential on the citation count, regardless of the research field and publication period. Concerning AAS, the impact of the videos referencing the articles was the most eminent in mathematics and computer science, while the most effective purpose was to explain the articles in 2019 and disseminate the publication in 2014 in life and earth sciences.

Assuming the growth model for the population of YouTube score and the citation count, we validated that the distribution of YouTube score saturates after 1.5 years from publication, and the view counts of article-mentioning videos grow faster than the citation counts. In mathematics and computer science, we found a significant correlation between the citation count and the YouTube score within the article groups with the explanatory and supplementary videos, suggesting the possibility of predicting the future citation count of articles in the early stage of publication with the YouTube score of the same video method. On the other hand, we could not identify any video method that showed a significant correlation in life and earth sciences, suggesting that the proposed prediction method was ineffective.

Videos were produced for more or less than only 1\%of the articles within one year of publication, implying that article-mentioning video remains a minor science communication method. In mathematics and computer science, there was no significant difference between 2014 and 2019, while in life and earth sciences, there was a significant increase in 2019 compared to 2014, confirming the case where the scientific events with high affinity to videos have a significant impact on the activity of science communication on YouTube. Furthermore, the articles with videos tend to be concentrated in highly cited sources, indicating that the frequency of science communication on YouTube depends on the source's citation rate.

This study verified that YouTube videos effectively contribute to the article's citation count and Altmetrics and identified effective video methods for each index. For articles in the early stages of publication under certain conditions, we could partially estimate the effective video methods for predicting the future citation count using video's popularity.

\section{Future Work}

We can consider applying the proposed method to articles related to specific research topics to verify academic video's impact on individual topics. In this experiment, due to the scarcity of the videos, we used articles in a broad academic field and validated the video's impact on a wide range of research topics. However, with prospects of an upcoming increase in the number of academic videos, the experiments with an article set focusing on a specific topic will enable researchers to obtain more realistic and reliable results.

To improve the method, we can devise a more effective homogenization method for articles with and without videos, define a new taxonomy of video method to observe more significant differences in impact between subdivisions and redesign the YouTube score to better account for differences in the impact on the article by video method.

Finally, the proposed method mainly uses statistical hypothesis testing by grouping the articles and has the limitation of discussing only the macroscopic effects of article-mentioning videos. Based on the dynamics surrounding YouTube and behavioural theories among users, we expect further research to approach the more microscopic interactions between online academic videos and articles, delving into the causal relationships between them.