Gender Differences in Using YouTube as an Educational Platform: A Case Study

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ABSTRACT

YouTube is ranked as the third most popular website in the world with more than 1 billion unique users visiting the website each month[1]. Beside entertainment content, YouTube houses a huge amount of educational videos spanning a wide range of areas from art and literature to astronomy and physics. Since the educational content on YouTube is ad hoc in nature and far less structured compared to what Massive Open Online Classes (MOOCs) have to offer, the number of studies on the behavior of self-learners on this platform is notably smaller than similar studies on MOOCs. In this work, we focus on YouTube as an educational environment for learning and discussing new materials, and in particular, we study gender differences in the viewership as well as the participation of users in discussions.

Keywords

Online Education, YouTube, Students' Engagement, Gender Differences

1. INTRODUCTION

The rapidly growing popularity of YouTube has made it the third most visited website in the world[2]. Although entertainment videos make up most of YouTube's content, the number of educational videos on YouTube is rapidly increasing. In fact, YouTube has witnessed an unprecedented growth in the number of users who watch educational videos. For instance, the number of subscribers to educational YouTube channels tripled in 2013. Note that YouTube makes it possible for users to interact through posting comments and replying to others. This makes YouTube quite similar to an educational platform on which students can engage in scientific discussions.

Despite being an influential educational platform, YouTube has been mostly overlooked by researchers interested in online education. For instance, while students' engagement in Massive Open Online Classes (MOOCs) has been extensively studied, one can barely find a similar study for YouTube. This is mainly due to the fact that educational content on YouTube is of a different nature compared to what MOOCs have to offer. MOOCs provide a set of well-structured materials that aims to cover a particular syllabus. On the other hand, YouTube mostly consists of relatively short, and stand-alone videos each explaining a scientific concept. Despite these difference, the massive role of YouTube in self-education is undeniable. In this work, we focus on the dynamics of YouTube as an educational environment. More specifically, we study how gender affects the participation of users in online discussions.

Outline: The rest of paper is organized as follows. Section 2 summarizes the existing literature related to our work. Section 3 describes the dataset as well as the data-collection process. In Section 4, we study the engagement of users with educational content on YouTube, and we highlight gender differences in how users view and comment on videos. Finally, we conclude the paper in Section 5.

2. RELATED WORK

To the best of our knowledge, this is the first work to study the gender differences in how self-learners engage with educational content on YouTube. Nevertheless, our work is related to many studies in computer science, sociology, and education science. These studies can be grouped into three main categories which are listed below.

Studies on YouTube as an educational tool: There is a body of literature that investigates how educational YouTube videos can improve learning in different areas such as Anatomy, Nursing, and Health education [1–4, 6, 9]. For instance, the work of Jaffar [9] studies how a group of medical students viewed and rated a number of suggested YouTube videos on anatomy, and concludes that YouTube can indeed enhance anatomy learning. Note that these studies mostly consider YouTube as a source for supplementary materials that can be used along with the materials provided in the classroom. Our work, on the other hand, is one of the few that studies the potential power of YouTube as an educational platform on its own. In that regards, the work by Lee et. al. [11] is closer to our study as it focuses on the benefit of employing YouTube to teach procedural instructions for various task. A key aspect that separates our work from the related work mentioned above is the focus we put on studying gender differences in this educational platform.

[1]http://www.youtube.com/yt/press/statistics.html
[2]http://www.alexa.com/topsites

Table 1: Statistics of selected channels

	Subs-criber	Total view	Tot vids	Subject	Edu Gen
Brain Scoop	260 K	9.3 M	101	Biology	F
Crash Course	2,702 K	162.7 M	273	History Literature Psychology Biology Chemistry	M
Minute Physics	2,681 K	184.5 M	120	Physics	M
Number-phile	1,146 K	81.8 M	146	Math	M/F
Physics Girl	52 K	4.2 M	30	Physics	F
Vihart	827 K	45.7M	51	Math	F

Studies on role of gender in YouTube: The study of gender roles on YouTube has received a lot of attention from researchers in the areas of education science and cyber psychology [8, 13, 14, 16, 17]. This line of literature studies the gender differences in presence and activity of users on YouTube as a social networking platform. For instance, the work of [13, 14] studies to what extent female users create YouTube content (in forms of video blogs) compared to male users. Although this line of research is related to our work, we are focused on and interested in the educational videos and the engagement of users with such content on YouTube.

Studies on students' engagement in online courses: There is a rich body of existing work on how students participate in online classes and engage with the educational materials [5, 7, 10, 12, 15, 18]. These studies mainly aim to understand why many students fail to complete courses on the MOOCs. Nevertheless, they provide valuable insight on what style of presentation and what type of content is more likely to keep students motivated to complete the online courses.

3. DATA COLLECTION

For our data-analysis task, we selected 6 popular science-channels on YouTube and focused on their content. Our criteria for selecting these channels can be described as follows: (1) We were interested in channels with many videos and a large volume of subscribers, (2) The selected channels had to include both male and female educators (also known as YouTubers), and (3) our selection had to cover various areas of science. Table 1 shows the selected channels and some general information about them. The last column of the table shows the gender of the YouTubers. Note that the `Numberphile` channel includes some videos lectured by men and some videos lectured by women. Also note that unlike other channels, `Crash Course` covers multiple subjects. The videos in this channel are organized into different playlists each covering a distinct subject. Furthermore, videos in each playlist are ordered by episode numbers, and the viewers are encouraged to follow the videos in the suggested order.

From the channels listed in Table 1, we collected 721 videos and about $970K$ comments in total. The comments on each video were retrieved through the YouTube API. Unfortunately, YouTube only returns a limited number of comments on each video. More specifically, one can retrieve around $3,000$ of the comments posted on each video. Beside posting comments, users can reply to other's comments. We refer to a comment and its corresponding reply messages as a *discussion*. For all comments that initiated a discussion, all the reply messages[3] are also collected. As a part of our data-collection process, we also extracted a set of features for each educational video. More specifically, we recorded the total number of views, comments, likes, and dislikes of each video, in addition to the title, the publish date, and the duration of all videos. Moreover, the transcript of each video was collected which we used to measure (in words per second) how fast each educator speaks. This dataset is publicly available online[4].

3.1 Gender Identification

Of course, the first step towards studying gender dynamics on YouTube is to identify the gender of users who interact with each other by leaving comments. This can be done by looking at the first name reported by each user. There are various packages and services to predict the gender based on a given first name. For our experiments, we use a python package called "sexmachine"[5] which simply looks up the gender of a given name in a list that contains more than $40,000$ names. If a name is either unisex or absent from the list, the package reports the gender as unknown. Unfortunately, we can only predict the gender of 32% of all users as they normally tend not to use their actual names on the website. Nevertheless, we show that these predictions are both accurate and sufficient for our data-analysis task.

Gender	Prediction Outcome: Male	Female	Unknown	Total
Male	2060	29	854	**2943**
Female	10	134	53	**197**

Figure 1: The confusion matrix for gender prediction

To evaluate the obtained accuracy, we created a ground-truth dataset as follows. Each YouTube account is associated with a Google+ profile on which users may report their gender. Although most users choose not to do so, we can occasionally find profiles with gender information. To obtain a ground truth, we randomly selected 6 videos, collected the Google+ profiles of all users who commented on them, and searched their profiles for gender information. Among $3,140$ users who reported their gender, the sexmachine made a prediction for $2,233$ users with less than 2% error. Figure 1 shows the confusion matrix for our gender-prediction task. Note that the gender ratio of users for whom we were not able to make any predictions is the same as the overall gender ratio[6]. Thus, we can safely use our predictions to estimate the gender ratio of users who interact by leaving comments.

[3]Reply messages can be retrieved through the Google+ API.
[4]`http://cs-people.bu.edu/ghasemi/youtube.tar.gz`
[5]`https://pypi.python.org/pypi/SexMachine`
[6]Gender ratio is defined as ratio of males to females.

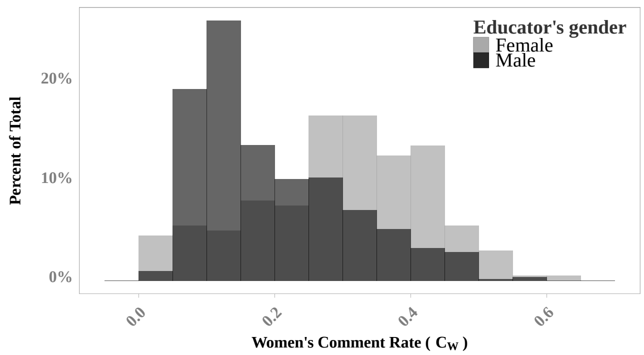

Figure 2: Distribution of women's comment rate for videos by male and female YouTubers

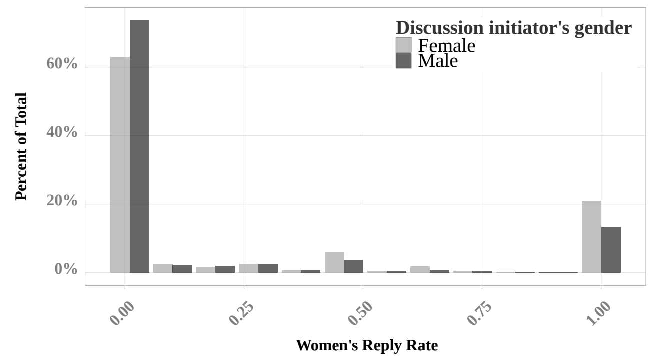

Figure 4: Distribution of percentage of replies by women in discussion initiated by male and female users

4. DATA ANALYSIS

In this section, we study what affects the engagement of users in online educational videos. Specially, we try to highlight scenarios in which women show a high degree of participation. We start by discussing a set of experiments that help answer some fundamental questions about users behavior. Then we use our first set of findings to design a more controlled experiment and gain a better insight about gender dynamics on YouTube.

4.1 Primary Data Analysis

There are two basic measures for evaluating the engagement of women in an educational video: (1) The ratio of female viewers, and (2) the ratio of comments posted by female users. Since viewer demographics is not publicly available on YouTube, we rely on comments to study women's involvement in educational videos.

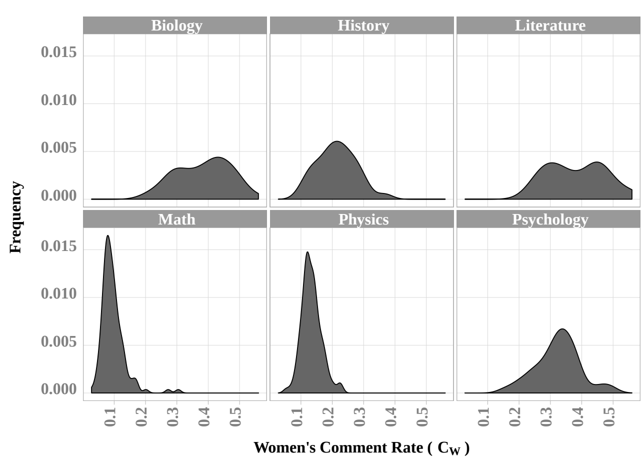

Figure 3: Distribution of women's comment rate across different subjects

Before presenting our data-analysis results, we need to introduce a bit of notation. For each video, we use C_W to denote women's *comment rate* which is simply defined as the ratio of comments posted by female users. Similarly, C_M is used to denote men's comment rate (i.e., $C_F + C_M = 1$). Note that values C_W and C_M are not known to us since we are not able to identify the gender of all users. However, as we discussed in Section 3.1, these values can be estimated quite accurately, and we use these estimations throughout our experiments. We present our first set of experiments as a series of questions that our data can help us answer.

Does YouTubers' gender affect women's participation?
Figure 2 shows the distribution of women's comment rate (C_W) for videos by male YouTubers (dark gray), as well as female YouTubers (light gray). We can clearly observe that women engage more in videos lectured by female YouTubers. For instance, women's comment rate exceeds 0.25 in 70% of the videos by female YouTubers, while this happens in only 30% of the videos posted by men. Another important observation is that women's comment rate rarely exceeds 0.5 which implies that women are underrepresented on YouTube. In fact, our collected dataset shows that the average comment rate for women is only about 0.22.

What subjects tend to interest women more?
To answer this question, we plot the distribution of women's comment rate for videos on each subject. However, to control for the bias that YouTubers' gender creates, we only focus on videos by male YouTubers. Figure 3 summarizes our results. Note that educational videos on Psychology, Biology and Literature show a higher degree of women's participation compared to other areas. Furthermore, we can observe that women's comment rate in Math and Physics is extremely low (i.e., roughly 1 in 10 comments).

Do women engage more in discussions initiated by women?
As we mentioned earlier, YouTube users can reply to comments, to create discussions. Each discussion consists of an initial comment around which the conversation will be based. For this experiment, we first computed the percentage of replies posted by female users in each discussion. Then, we created histograms showing the distribution of these reply rates for discussions initiated by men, and women separately. Figure 4 shows both histograms in a single plot. We can observe that most discussions are dominated by one gender or the other. Moreover, we can see that discussions initiated by women are more likely to receive more replies from women.

Finally, we would like to point out that besides the aforementioned experiments, we also examined the relationship

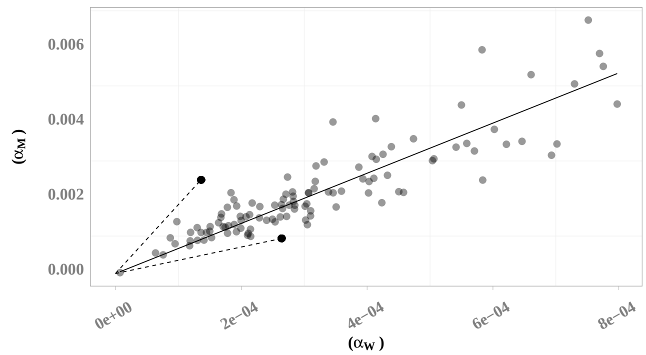

Figure 5: Relationship of activity rate of women to men in Minute Physics videos

between women's comment rate and a number of video attributes such as duration, pace, and popularity (measured by number of views and/or number of likes), but we were not able to find any significant correlations.

4.2 Model-Based Data Analysis

To continue our analysis of gender dynamics on YouTube, we need to make some basic assumptions about our dataset. To do so, we suggest a simple and intuitive generative-model that explains the observed ratio of comments by male and female users. Based on this model, we set up an experiment to control the effects of subject and YouTubers' gender on women's participation.

Generative Model: Each video on YouTube receives some number of views V from both male and female users. Let us use V_M, and V_W to denote these view counts respectively (i.e., we have $V = V_M + V_W$). A subset of these viewers choose to leave a comment. To model this, we define an *activity rate* for both male and female viewers (denoted as α_M and α_W) which are simply the probabilities that each male and female viewer would comment on the video. Based on this model, the total number of comments posted by female and male users (denoted as N_W and N_M respectively) can be written as $N_W = V_W.\alpha_W$ and $N_M = V_M.\alpha_M$. Finally, it is important to note that all parameters in this model (e.g., V_M, V_W, α_M and α_W) are video-specific (i.e., their value might change from one video to another).

Discussion: At a first glance, the suggested model may not seem helpful at all since none of its parameters (e.g., V_M, V_W, α_M, and α_W) are known to us. However, there are two main reasons for why this model is appealing:

(1) Focusing on activity rates (α_W and α_M) as opposed to comment rates (C_W and C_M) provides a way to control for the effects of subject and YouTubers' gender. To see this, consider a video on mathematics that was watched by 990 male users and only 10 female users. Now, even if all 10 female users leave a comment on this video, the comment rate would probably be small, while the activity rate can effectively highlight that all female users engaged with the video content.

(2) Although we are not able to compute the activity rates, we show that our dataset can be used to identify the videos

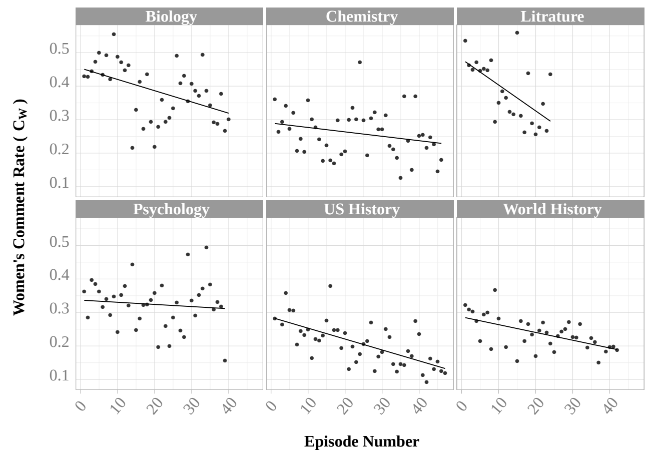

Figure 6: Changes in women's comment rate based on episode number

in which women's activity rate is relatively high. This set of videos can be used to determine what other factors affect women's participation.

Further Analysis: As we mentioned earlier, the demographics for YouTube videos are not publicly available. As a result, we are not able to compute gender-specific view counts V_W and V_M. However, we can assume that the ratio of female viewers (which we denote as $f = V_W/V$) stays roughly the same across the videos of a single YouTuber on a single subject. This is a reasonable assumption as YouTube channels are normally followed by a stable community of subscribers. Based on this assumption, we can show that the activity rates of female and male users should be proportional to the following values.

$$\alpha_W = \frac{N_W}{f.V} \propto \frac{N_W}{V} \tag{1}$$

$$\alpha_M = \frac{N_M}{(1-f).V} \propto \frac{N_M}{V} \tag{2}$$

Using the above equations, we can study the relationship between the activity rates of male and female users by comparing N_W/V and N_M/V values. Figure 5 shows the distribution of these values for all videos from the `MinutePhysics` channel. Note that the activity level of male and female users are highly correlated, and we can fit a line to describe the relationship between men and women's activity rates. However, we can occasionally find videos for which the observed activity levels deviate from our expectation. Figure 5 shows two example of such videos (i.e., the points with darker shades). The point that appears at the top corresponds to a video in which women's activity rate is higher than expected, while the other point indicates an unexpected high value for men's activity rate.

To study the nature of videos with unexpected activity rates for both men and women, we set up the following experiment. From each channel, we picked 10% of videos with highest degree of deviation from the best fitted line that correspond to high activity rates by women. Similarly, we also picked 10% of videos with unexpected high activity rate by men. Using this technique, we created two set of videos where each contain roughly 70 videos that were successful in terms of engaging users of a particular gender. By focusing on these set of videos, we observed an interesting trend; Among the 70 videos with high women's activity rates, 20 videos correspond to early episodes of different playlists (i.e., episodes 1 to 10). The corresponding number for the other set of videos is only 3. To validate this pattern, we plotted women's comment rate against videos' episode number for each subject. Figure 6 shows our results obtained using the set of playlists from the `Crash Course` channel. We can observe that the slop of fitted lines is negative which confirms that the activity rate of women tends to be higher in the early episodes of an educational series.

Finally, we would like to point that the above analysis only serves as an example to highlight what sort of trends can be discovered through our proposed model-based analysis.

5. CONCLUSION

In this paper, we studied the dynamics of YouTube as an educational platform. Specially, we studied which factors can affect the women's participation in online discussions. Beside presenting our empirical findings, we proposed a generative model which we used to develop a model-based analysis method. Finally, we used our model-based analysis to learn more about the engagement patterns of YouTube users. Our results highlight that the content created by female YouTubers tend to attract female users. Similarly, we observe that women tend to participate more in discussion that are started by female users.

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