



# Music on YouTube: User engagement with traditional, user-appropriated and derivative videos



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## ABSTRACT

YouTube is the leading Internet video service and one of the most popular websites in 2014. Music videos hold top positions in different YouTube charts, but the music video types or engagement patterns with them have not been systematically studied. In this paper we present three studies that focus on YouTube music. We first show that music videos are the most popular content genre in YouTube. We then present a typology of traditional and user-generated music videos discovered in YouTube. It includes twelve subtypes of music videos under three main types: traditional, user-appropriated, and derivative. Last, we present findings on user engagement statistics that go beyond view, comment, and vote counts. These metrics show that while music videos gather more views, engagement differences with other content genres are miniscule. However, there are notable differences in engagement between different music video types. This is prominent between different artists on one hand, and between traditional and user-generated videos on the other. We synthesize these findings by discussing the importance of user-generated videos in YouTube's music ecosystem.

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## 1. Introduction

Watching videos has become one of the most popular activities in the Internet. According to ComScore, 1.3 billion people watched online videos in 2013, viewing on average 162 videos every month (ComScore, 2013). YouTube is currently the most popular video service and the third most popular Internet service overall according to Alexa.com (November, 2013). YouTube was used by at least 758 million users around the world every month, with each visitor watching 79 videos on average each month (ComScore, 2013).

One of the reasons for YouTube's success may be in music content, which has a prominent place in the service. In 2013, YouTube was the most recognized digital music brand (IFPI, 2014). 38.4% of YouTube's traffic relates to music (ComScore, 2013) and 23–30% of its videos bear the "Music" categorization (Cheng, Dale, & Liu, 2007; Gill, Arlitt, Li, & Mahanti, 2007). Academic research also indirectly acknowledges the importance of music among the different types of content (Broxton, Interian, Vaver, & Wattenhofer, 2013; Burgess & Green, 2009; Cunningham & Nichols, 2008).

However, although music enjoys vast popularity in computer-related behaviors, it remains an underinvestigated topic. There

are studies on music and media consumption patterns (Baur, Büttgen, & Butz, 2012; Sease & McDonald, 2011; Voids, Grinter, Ducheneaut, Edwards, & Newman, 2005) and on music information retrieval (Cunningham & Masoodian, 2007; Cunningham, Reeves, & Britland, 2003; Downie, 2003), but, to our knowledge, two topics have remained unaddressed in academic research. Despite YouTube's prominent role in music industry, research has not quantified the importance of music listening in YouTube in comparison to other content genres. Second, it remains unknown whether there are differences in viewing and listening patterns between music and other content genres on one hand and between different types of music videos on the other. Given YouTube's position as the most recognized digital music brand, and music's prominence in the service, we find that these two unaddressed topics deserve more attention. Our study is one of the first studies in this area. With these analyses, the picture about online music listening and watching can be sharpened.

Our paper analyses the most popular cases of music interaction in YouTube with a specific focus on users' interactions with recorded music. Our research approach is *music first*, that is, we consider videos primarily through their audio content. We look for answers to the following research questions:

(RQ1) *How popular is music in comparison to other genres on YouTube?*

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- (RQ2) What are the types of music content on YouTube?  
 (RQ3) How do users engage with YouTube videos across different genres and different music video types?

We present three studies utilizing both qualitative and quantitative methods. Overall we find that users have extensively appropriated YouTube for music use. In YouTube context, our notion of user appropriation refers both to the re-invention of a technology's purpose of use by its users and the claims for ownership and control of its use (e.g., Eglash, 2004; Mackay & Gillespie, 1992). In YouTube, users continuously take control of original video content and re-use it to create their own video versions. Therefore, from re-invention point of view, users have created a music-first, audio-oriented "video" formats inside YouTube that support music listening.

The contributions of this paper are three-fold. First, given the constant change of digital music consumption, we provide a historical snapshot of music interaction with recorded music on YouTube in 2013–2014. This reveals the importance of music among YouTube's content categories. Second, we show that the music content in YouTube needs to be considered bearing in mind its sub-types, since the users' interaction patterns between the subtypes differ significantly. Third, our results suggest that the adoption of YouTube for music interaction has been facilitated by a phenomenon that we call the "halo effect." It explains how user-created videos surround and flourish next to original, professionally-created music video releases. We present our findings in three empirical sections after the following background section. With this pioneering exploration, we hope to open up new research questions for studies of music interaction and fuel discussion about the role of "users" in professional media production and distribution in the 21st century.

## 2. YouTube and music

YouTube was founded in 2005 and acquired by Google in 2006. YouTube started with the intention of allowing regular users to publish their videos, but it has gradually developed into a professional media outlet, mixing free and subscribed content on an advertising-friendly platform (Burgess & Green, 2009; Kim, 2012). Currently it delivers prominently professionally generated content (Kim, 2012). It is also common for users to upload copies of professional content, i.e. user-copied content (Ding et al., 2011). This collective effort creates multiple, not necessarily totally identical copies of the original professional content (De Oliveira, Cherubini, & Oliver, 2010), sometimes appearing months after the original release (Cha, Kwak, Rodriguez, Ahn, & Moon, 2007), only to disappear later (Prellwitz & Nelson, 2011).

Over the past nine years, YouTube's popularity has reached huge proportions. YouTube has announced that 100 hours of video are being uploaded to its service every hour and that its Content ID for tracking copyrighted material has been used on over 200 million videos (YouTube, 2013a). However, the total number of videos has not been publicly disclosed. An academic study from late 2010 estimated the number to be 448 million (Ding et al., 2011). YouTube user EducateTube.com estimates that almost 3 billion videos had been uploaded by late 2012.<sup>1</sup> Considering the wealth of user-generated, non-copyrighted material that does not have a Content ID, it is likely that there are over one billion videos in the service. This means that any data about YouTube is bound to be "big" in volume and velocity (Stonebaker, 2012), and challenging in terms of sampling (see Blythe & Cairns, 2009).

<sup>1</sup> Video "How many videos are on YouTube?" by EducateTube.com (<http://www.youtube.com/watch?v=jpYCU22l-E>), accessed 13th November 2013.

### 2.1. The YouTube user interface

YouTube's user interface influences the kind of experiences people can attain from it (Blythe & Cairns, 2009; Buie & Blythe, 2013). Knowledge of the present YouTube interface is central for understanding the research results thus we describe it here.

The viewing experience is centered around the web interface and the video player page. Parallel, alternative interfaces for mobile devices are also available (i.e., mobile applications and a mobile web site). YouTube video entries have two facets, *media* (video, thumbnail, and title) and *basic statistics*, that are consistently presented together. Fig. 1 shows the appearance of the "desktop" browser based video player in late 2013.

The primary component of the page is Player. Using the *Player* to watch content, user can pause the playback, choose a resolution, change volume, and jump to a different point in time. When the video finishes, user input is required to continue watching. Registered users can save playlists, which enables them to playback multiple videos sequentially. Registration is also required for viewing any rated content. Advertisements of 5–30 s may be embedded in the beginning. The existence and content of ads, and the video access depends on the user's region.

In addition to the Player, the user interface has four other main components: Search bar, Suggested content column, Metadata and voting controls, and Comments area. The Search bar allows users to perform keyword-based queries. The results are delivered on a separate Search results view. Search results can be filtered according to several criteria. Suggested content column, filled by recommended videos and advertisements, is to the right of the other components.

Metadata and voting controls reside right below the Search bar. They include both the description provided by the uploader and the basic viewing statistics. The number of total views is the central gauge of popularity in YouTube, appearing systematically next to the videos in search results and other listings. The space below is dedicated for the number of user votes (i.e., the count of thumbs-up and thumbs-down) and a bar visualizing their balance. In addition to basic statistics, YouTube collects detailed Analytics data. The uploader can make some of these extended statistics visible below the basic statistics.

Logged-in users can rate the video by voting thumbs-up or thumbs-down and subscribe to the uploader's *channel* to receive updates about activity on the channel. Channel subscription is therefore an important measure of user engagement as it reflects a sustained interest in the channel (Tang, Gu, & Andrew, 2012). The final section is the Comments area populated by input from logged-in users.

### 2.2. Literature on music use of YouTube

In order to support our claim of lack of prior work and to justify our choice of methods, we present a review of the essential literature.

The academic interest in YouTube is in a steady a rise. A citation report from Thomson Reuters Web of Science (May 2014) for publications including "YouTube" as their title ( $N=492$  by 2014) shows a linear increasing trend every year since 2006, with over 100 papers recorded for 2013. The majority of the papers are from medical journals and they typically assess medical information or health phenomena in YouTube videos (see, e.g., Lewis, Heath, St. Denis, & Noble, 2011; Steinberg et al., 2010). Content analysis has also been practiced in human-computer interaction studies. Blythe and Cairns (2009) pioneered this work by analyzing YouTube videos to understand the portrayals of iPhone 3G. They used content analysis to categorize hundred videos into seven categories (e.g., review, reportage, unboxing, and demonstration).

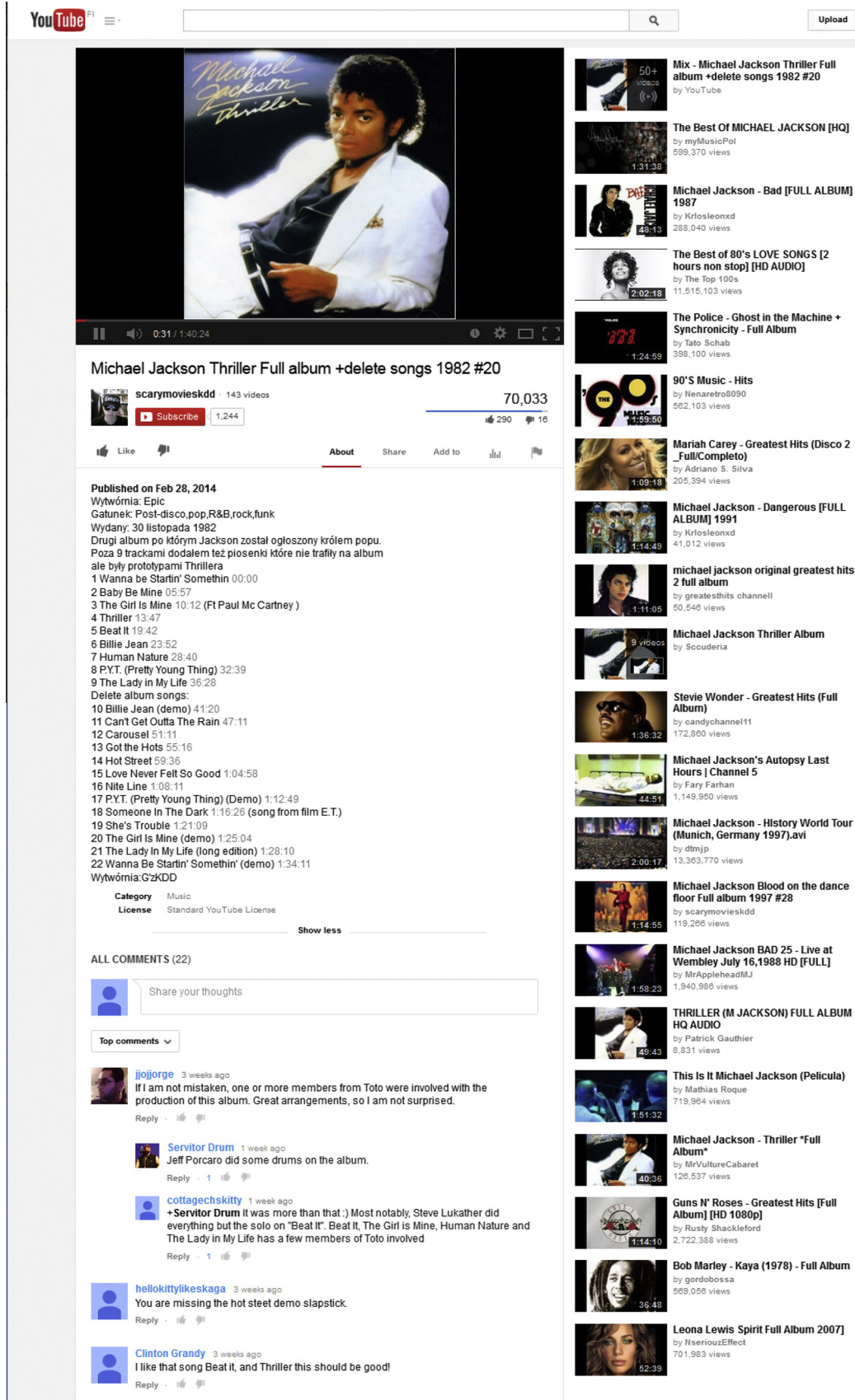


Fig. 1. The YouTube player interface. The screenshot for video from 4/30/2014 shows the main interface elements visible in a desktop browser view.

They also discussed the genre of satire, and analyzed one parody video in length using a grounded theory approach.

The most cited reference in the domain, according to Google Scholar, is the book by Burgess and Green (2009) on YouTube's participatory media culture. Burgess and Green examine different aspects of user-generated content. They also contrast today's new broadcast era with the past, highlighting the performative nature of this new medium. Using YouTube's public statistics to measure audience interactions, the book presents data on the number of views, subscribers, and favorites to show that user-generated content prevails on YouTube. Overall, they frame YouTube in a positive way, emphasizing its function for empowerment and emancipation of citizens in an otherwise corporate-controlled media space.

Most of the YouTube studies do not give an emphasis to behavior around music. A recent study that quantified music interaction habits among Finnish youth, found YouTube being the most frequently used music service that many use daily. YouTube was also used to complement Spotify listening and for sharing music (Liikkanen & Aman, 2015). Another focal example looked into how students find videos. It showed that YouTube was the primary source for video search and music was the most frequently sought content category. In the typical case, users first searched and then continued by browsing the related videos (Cunningham & Nichols, 2008). It has been elsewhere documented, using both disclosed (Liikkanen, 2014) and proprietary data (Broxton et al., 2013), that people access music videos mostly through YouTube Search.

Previous research shows that most music videos are available in several copies, some in several thousand (Prellwitz & Nelson, 2011). The duplicates help to circumvent the fact that videos tend to disappear within 9–18 months. The reasons for removal are most often related to copyright violations (49%) or discontinued user accounts (23%; Prellwitz & Nelson, 2011). In other papers that look into YouTube's musical content, it has been described how Bulgarian popular music *chalga* has been distributed through different media, including YouTube and a derivative service, ChalgaTube (Kurkela, 2013) and how YouTube may influence the careers of aspiring musicians (Cayari, 2011).

### 2.2.1. How do uploaders and commenters behave?

User behavior on YouTube is often studied from the video creation and publication point of view, possibly driven by the interest in new forms of online content creation, sharing, and remixing (e.g., Lessig, 2008). This is somewhat controversial, because uploading is an uncommon behavior; it has been estimated that only 11% of all YouTube users upload content (Ding et al., 2011). A study among subscribed YouTube users ( $N = 1,467,003$ ) clustered 23% of them as "content producers" (Maia, Almeida, & Almeida, 2008). The conclusion is that studies of uploaders, such as Lingel's (2010) study of live music video uploaders and their metadata practices, are focused on marginal user groups.

The second most studied behavior in YouTube, after video creation, is commenting. We know for example that music is among the least discussed categories (Thelwall, Sud, & Vis, 2012) and that commenting on YouTube is different than in Facebook. A study on political expressions (Halpern & Gibbs, 2013) showed that YouTube comments were less polite and less often justified than Facebook comments. Additionally, off-topic messages in YouTube were longer than those in Facebook (Halpern & Gibbs, 2013). YouTube is therefore more similar to Twitter as a social network than to Facebook (Wattenhofer, Wattenhofer, & Zhu, 2012).

A recent study analyzed comments for YouTube meditation videos (Buie & Blythe, 2013). It categorized comments into religious, secular, and new age, and additionally classified the comments as 70% positive, 20% negative, and 10% neutral. The comments providing advice, explanations, or support were more

numerous among the top comments (i.e., the comments that were most liked). A study that sampled over a million comments arrived in similar conclusions (Thelwall et al., 2012): comments are generally positive, but the negative comments evoke most responses. This may reflect the phenomenon known as "flaming", the posting of offensive or hostile comments (Moor, Heuvelman, & Verleur, 2010), behavior also known as trolling.

### 2.2.2. Content and popularity

Question about the balance of user vs. professionally-generated content on YouTube has inspired many researchers. Kruitbosch and Knack (2008) found that professionally-generated videos dominate the most viewed videos, but in a random sample, user-generated videos were more numerous. What is this user-generated content like? Ding et al. (2011) showed that 63% of popular user channels published "user-copied content" instead of authentic user-generated content. Most uploaders consistently uploaded either type. However, the most popular user-generated content exceeded the most-popular user-copied content in popularity.

This brings out the fact that multiple, nearly identical copies of the same content exist on YouTube. De Oliveira studied near-duplicate videos on YouTube (De Oliveira et al., 2010), showing that people consider audio, video, and semantics in similarity judgments. Users were generally more tolerant towards audio changes than differences in video. On the other hand, users were sensitive to the identity of music, preferring the original music to a cover version.

YouTube has become known for viral videos that get a lot of views in a quick succession. This has sparked research on how popularity is gained and maintained. An important factor for a video's popularity is its visibility inside YouTube and in Google search results (Figueiredo, Benevenuto, & Almeida, 2011). It is known that the most video views originate from two sources: YouTube search and Suggested content (Liikkanen, 2014; Zhou, Khemmarat, & Gao, 2010). Social sharing also generates popularity quickly, but the attractiveness of these "social videos" also wears off more rapidly than those of less frequently shared. Different types of content are shared differently, videos in "Pets & animals" genre category having the most of highly shared videos (42.3%), whereas music videos are shared less frequently (12.8%; Broxton et al., 2013). Sharing patterns may partially explain why most YouTube videos capture only a geographically constrained audience (Brodersen, Scellato, & Wattenhofer, 2012).

### 2.2.3. Implications for the present study

This review has demonstrated that there is little research relevant to understanding the music use of YouTube. For instance, music listening behaviors, music video formats, and music interaction patterns are poorly known.

Based on the presented literature, we will seek to answer our research questions by first surveying different popularity measures, then qualitatively analyzing popular video content, and finally adopting a quantitative approach to measure the engagement for some videos types that we discovered in the qualitative analysis.

## 3. Study I: the relative popularity of music on YouTube

Our first research question addresses the popularity of music in comparison to other YouTube content genres. This is a foundational question to contextualize the whole research topic. Answering this question sounds simple at first. Popularity could be measured with respect to total time that users have spent watching videos or by the number of search requests for the videos of each genre. Unfortunately data about such measures is publicly

unavailable. In the absence of such data, we relied on the following three secondary data sources:

- Search term trends used within YouTube, based on the Google Trends service (Google, 2013).
- The list of most viewed videos provided by YouTube (YouTube, 2013b).
- The statistics on the most popular YouTube channels gathered by third-party services.

These data sources have variable validity. The Google Trends data for Web search has been previously demonstrated to be a valid predictor of music consumption (Goel, Hofman, Lahaie, Pennock, & Watts, 2010). YouTube's top video listing can be considered authoritative, but the validity of channel statistics has to be accepted at face value. Our method was to first retrieve these statistics, some of them with the help of YouTube API (versions 2 and 3), and then analyze them for the quality and quantity of music content.

### 3.1. Results

Google Trends data from January 2008 to October 2013 showed the prevalence of music in search terms. In Google Web search trends, 70% of the most popular search terms ( $N = 14$ ) included artist names or were related to music (see Table 1). In YouTube, music was even more prominent. 74% of the most popular search terms referred to artists directly, and an additional 12% were music-related (e.g., “dance” and “musica”) – altogether 96%.

Music also dominates the list of all time *most viewed videos* provided by YouTube (YouTube, 2013b) shown in Table 2.

Of the most viewed YouTube videos, 19 out of 20 were artist's official music videos from the genre category of “Music.” On average, these music videos had 580 million views, 1.5 million comments, and 1.7 million thumbs-up votes.

We used Socialbakers.com to extract data about YouTube channel subscriptions and associated video statistics cumulated by fall 2013. We classified the orientation of Top 20 channels into: gaming, humor, music: artists, music: labels, and educational based on their content. Half (10 out of 20) of the most popular channels featured music (see Table 3). Six channels were associated with artists and four with record labels. Gaming and humor channels were the second and third most popular genres.

Table 3 shows that while the audiences for gaming video channels appear as the most engaged (based on the number of subscribers), music (i.e., artists and labels) and humor channels do not fall much behind. Artists' channels stand out as having a superior reach for audience, with their average views per video exceeding ten times the average of others.

### 3.2. Discussion

In all of the three measures of genre popularity in YouTube, music either dominates the charts or shares the top ranks. The findings about search trends show that people do not incidentally bounce into music while browsing YouTube; they intentionally look for it from web and especially from YouTube. These findings are compatible with earlier studies that have demonstrated the importance of search for accessing music videos (Broxton et al., 2013; Cunningham & Nichols, 2008; Liikkanen, 2014).

Music videos dominate the list of most popular videos. This was expected, given the similar results from 2008 (Burgess & Green, 2009). It differs from the current popular stereotype according to which the most popular video content in YouTube includes puppies, kittens, and babies. Table 2 shows only a single baby video among the most viewed titles. An unfortunate omission from this

**Table 1**

Most popular search terms used in Google Web search and YouTube search by content genre category (data ranges from January 2008 to October 2013).

Google Web search			YouTube search		
Category	Number of terms	%	Category	Number of terms	%
Music related <sup>a</sup>	11	55	Artist	37	74
Artist	3	15	Music related	6	12
Other	3	15	Other	2	4
Service	3	15	Ambiguous	4	8
Ambiguous	0	0	Gaming	1	2
Total	20		Total	50	

<sup>a</sup> Includes music services.

analysis, resulting from a necessity to use secondary data sources, is the lack of information about audience demographics. Influence of American culture is however evident in the results. YouTube has stated that although the most popular music videos are North American, their audience is mostly from outside of North America (YouTube Trends Team, 2013).

Resuming the comparison to Burgess and Green (2009) we can say that while the content categories have retained their relative popularity, there seems to be a lot of fluctuation in the popularity of individual content channels. A comparison to the most popular channels in 2008 (Burgess & Green, 2009; Table 4.1) reveals that the top ten of the channels has completely transformed during the past five years. Also, there now appears to be less variation between the most viewed and the most subscribed channels than there was in 2008; same channels now occupy both lists. Second, professionally managed channels have taken the stage from the so-called “homegrown YouTube ‘stars’” (Burgess & Green, 2009, p. 59). Artists (e.g., My Chemical Romance, Linkin Park, and Britney Spears) and music brands (UMG and SONY BMG) were doing well on the chart of the most viewed channels in 2008, but in 2013, the record company brands were gone and new artists (see Table 3) had replaced the old favorites. The only channel found in both 2008 and 2013 lists is Smosh, a comedy channel.

Overall, our findings challenge some of the results of Tang et al. (2012) who found that a third of the most popular channels were established in 2006 and 91% of them before 2010. This was interpreted as a “first-mover advantage.” We observed that new artists' channels still today have the capacity to rocket to the list of most subscribed and viewed channels.

## 4. Study II: types of music content in YouTube

In this study, we investigated the different types of music videos found in YouTube. In the absence of existing typologies of music videos, our research was exploratory. Our findings point to three primary types of music videos on YouTube, each with several subtypes.

Our approach was inspired by the Uses and Gratifications theory of media behavior (Haridakis & Hanson, 2009), which states that media use is goal-directed and that people select media to satisfy their needs. We also followed a *music first* principle, meaning that we built our framework from the perspective of music listening, making audio content the primary factor in the analysis, visual content secondary. Combining these two ideas, our analysis considered which user needs different types of videos might satisfy.

### 4.1. Methods

In this study, we analyzed the top YouTube search results for popular artists. We built upon the data of the most popular

**Table 2**

YouTube Top20 list of most viewed videos overall. For the descriptions of DisP, VpkV and CpkV statistics, see section 5.1.1. Source: [http://www.youtube.com/charts/videos\\_views?](http://www.youtube.com/charts/videos_views?) retrieved 30 September 2013.

#	Title	Views	Category	Comments	Likes	DisP	VpkV	CpkV	Min:Sec
1	PSY – GANGNAM STYLE (강남스타일) M/V	1780.4 M	Music	6,351,302	7,860,058	10.22	4.917	3.57	04:13
2	Justin Bieber – Baby ft. Ludacris	904.0 M	Music	9,562,023	1,901,778	65.75	6.143	10.58	03:45
3	Jennifer Lopez – On The Floor ft. Pitbull	694.0 M	Music	557,852	1,237,415	7.48	1.927	0.80	04:27
4	Eminem – Love The Way You Lie ft. Rihanna	600.5 M	Music	781,543	1,502,097	3.35	2.588	1.30	04:28
5	LMFAO – Party Rock Anthem ft. Lauren Bennett, GoonRock	574.5 M	Music	760,933	1,866,177	4.14	3.389	1.33	06:16
6	Charlie bit my finger – again !	565.8 M	Comedy	823,173	1,102,184	12.88	2.236	1.46	00:56
7	Waka Waka (This Time for Africa) (The Official 2010 FIFA...)	555.3 M	Music	940,259	664,490	6.05	1.274	1.69	03:31
8	PSY – GENTLEMAN M/V	552.9 M	Music	1,290,331	2,698,122	15.97	5.807	2.34	03:54
9	Lady Gaga – Bad Romance	536.4 M	Music	1,523,341	793,350	17.31	1.789	2.84	05:08
10	Michel Teló – Ai Se Eu Te Pego	526.1 M	Music	381,442	979,908	9.15	2.05	0.73	02:46
11	Carly Rae Jepsen – Call Me Maybe	498.3 M	Music	721,278	1,680,502	7.26	3.637	1.45	03:20
12	Eminem – Not Afraid	440.5 M	Music	1,417,548	1,602,081	2.66	3.737	3.22	04:19
13	Adele – Rolling in the Deep	434.3 M	Music	444,758	1,574,010	2.54	3.719	1.02	03:55
14	One Direction – What Makes You Beautiful	433.7 M	Music	1,205,672	1,692,114	10.75	4.372	2.78	03:27
15	Gotye – Somebody That I Used To Know (feat. Kimbra)	432.8 M	Music	538,231	1,872,041	3.99	4.505	1.25	04:05
16	Pitbull – Rain Over Me ft. Marc Anthony	431.8 M	Music	222,071	854,764	4.23	2.067	0.52	03:54
17	MACKLEMORE & RYAN LEWIS – THRIFT SHOP FEAT. WANZ	429.1 M	Music	440,404	2,172,734	3.68	5.256	1.03	03:53
18	Bruno Mars – The Lazy Song	419.5 M	Music	534,459	1,347,497	3.48	3.328	1.28	03:29
19	PSY (ft. HYUNA) 오빤 딱 내 스타일	414.1 M	Music	436,249	1,143,083	18.70	3.395	1.05	03:47
20	Katy Perry – Firework	389.1 M	Music	760,977	986,423	5.53	2.683	1.96	03:54
	Average	580.1 M		1,484,692	1,776,541	10.76	3.441	744.33	3:52

**Table 3**

Most popular YouTube channels (top) and aggregate measures by content genre category (bottom). Source: Socialbakers.com (<http://www.socialbakers.com/youtube-statistics/>), retrieved on 29 September 2013.

#	Channel	Subscribers	Video views	Category	Number of videos	Views per video
1	PewDiePie	13,530,789	2,486,241,740	Gaming	1468	1,693,625
2	Smosh	12,525,409	2,649,209,835	Humor	315	8,410,190
3	RayWilliamJohnson	10,284,334	2,516,271,686	Humor	604	4,166,013
4	Rihanna	10,117,833	4,100,279,163	Music: Artist	78	52,567,682
5	Machinima	9,411,985	4,502,101,675	Gaming	23,696	189,994
6	The Ellen DeGeneres Show	6,681,649	2,080,165,206	Humor	4470	465,361
7	officialpsy	6,467,532	3,191,490,666	Music: Artist	58	55,025,701
8	Eminem	6,293,503	2,621,786,890	Music: Artist	36	72,827,414
9	Rooster Teeth	6,252,080	2,423,293,822	Gaming	4609	525,774
10	Justin Bieber	6,025,669	4,004,126,891	Music: Artist	79	50,685,151
11	YOGSCAST Lewis & Simon	5,994,976	2,171,559,846	Gaming	2234	972,050
12	CollegeHumor	5,110,128	2,050,474,617	Humor	2093	979,682
13	IGN	3,526,514	2,704,744,488	Gaming	87,579	30,883
14	Lady Gaga	3,515,708	2,382,804,907	Music: Artist	74	32,200,066
15	Expert Village   Watch. Learn. Do.	2,110,863	2,841,160,886	Educational	139,126	20,421
16	Turkish Music – Türkçe Müzik	1,871,610	3,505,736,840	Music: Label	9566	366,479
17	Fueled By Ramen	1,741,586	2,045,030,808	Music: Label	1125	1,817,805
18	UltraRecords	1,707,593	2,341,643,920	Music: Label	1477	1,585,405
19	Shakira	1,648,731	2,127,605,537	Music: Artist	82	25,946,409
20	Atlantic Records	1,472,007	2,606,711,454	Music: Label	796	3,274,763
#	Category	Total subscribers	Total video views	Average views per subscriber	Total videos	Average video views
1	Gaming	38,716,344	14,287,941,571	369	119,586	682,465
2	Humor	34,601,520	9,296,121,344	269	7482	3,505,312
3	Music: Artist	34,068,976	18,428,094,054	541	407	48,208,737
4	Music: Label	6,792,796	10,499,123,022	1546	12,964	1,761,113
5	Educational	2,110,863	2,841,160,886	1346	139,126	20,421

YouTube search terms (Section 3.1), which we used to focus our efforts on the most popular artists and their videos.

The analysis proceeded iteratively, inspired by but not strictly following a grounded theory approach of qualitative analysis (Charmaz, 2006; Corbin & Strauss, 1990). We first created a tentative typology from two YouTube music search terms that named popular artists and their songs: “Nicki Minaj Super Bass” and “Lady Gaga Applause.” We inspected approximately 100 results from each search and developed a tentative typology based on this data and our prior knowledge. We then challenged this typology by testing it against a new validation corpus. We built this validation corpus using a list of 20 most searched-for artists and identifying the most popular search result (i.e., song) for each artist based on YouTube suggestions. We then searched for this title (artist–song

combination) in YouTube and retrieved the first 20 search results in the order of YouTube's relevance metric. This resulted in a corpus of  $20 \times 20$  video entries.

The video subtypes were classified based on *audio* content, *video* content, and *embedded information* (e.g., subtitles and annotations). Following the music first principle, the audio content was the decisive factor. Our classification was perceptual and relied on our ability to observe musical fidelity of the audio tracks. Given that pitch modulations are common in user-uploaded music (Plazak, 2012) and neither researcher possessed absolute pitch, this dimension was not observed. However, both investigators were experienced instrumentalists.

The other two components, video and embedded information, were somewhat easier to judge than musical fidelity. Video titling

was also observed. Titles often make claims about video content and influence users' navigation within YouTube, thus affecting YouTube's relevance measures. Some subtypes were recognizable from specific terms, such as "lyrics" or "cover" appended to the original title.

Two researchers coded the validation corpus independently using the tentative typology. Our initial agreement was very good ( $kappa = 0.84$ ). Researchers discussed disagreements and resolved them to produce a final, refined typology. The discussions prompted adding one subtype (fan-illustrated videos, a subtype of user-appropriated videos), otherwise the initial typology held. Additional subtypes among the primary type derivative were identified (e.g., karaoke versions), but were deemed not to require recoding of the corpus, because these instances were very rare. Instead, we grouped them under the "Other derivatives" type.

## 4.2. Results

We discovered three primary music video types: *traditional*, *user-appropriated*, and *derivative* music videos. In the first two, all three elements (audio, video, and embedded information) were aligned with the original audio track and its music video. In particular, in traditional and user-appropriated videos, the audio track was a copy of a traditional version (studio or live) and its video respected the original song or the artist. In derivative works, the audio, the video or both could differ markedly from the original music track. The three primary types had altogether 12 subtypes, as illustrated in Fig. 2.

### 4.2.1. Traditional music videos

Traditional music video refers to the original, "authentic" video. In these videos, the audio content matched the song's album or single release. Videos were professionally made and there was typically no embedded information. The main subtype was *Classic music video*, which were professionally created short films set to the music. These videos had been usually uploaded to YouTube by the artists' representatives (original release) or fans (user-uploaded copies). The titles of classic music videos usually contained the name of the artist followed by the song name. In some less frequent cases the audio content was a special version of the song created by the artist purposely to accompany the video content.

Artists sometimes release *alternative versions* of their video. In our corpus we found two versions of Adele's *Rolling in the Deep*. One of them was a classic music video while the other was titled as a "Studio footage" version. Both shared an identical audio track.

*Live versions* constituted the other prominent subtype. Most of the videos in this subtype were copies of TV broadcasts or professional live recordings. These contents were usually uploaded without user modifications. We found no user-created live bootlegs (i.e., unauthorized live recordings) in the corpus.

### 4.2.2. User-appropriated videos

User-appropriated videos included four subtypes. All of them retained the original audio content but their video content included user-created elements. Embedded information was commonly observed.

*Still videos* discarded the motion picture altogether and replaced it either with a still photo or a slideshow, related to the artist. We also found a still video variation that utilized YouTube's "deep linking" feature: the possibility to create links to specific points in time on the video. With this feature, users had uploaded entire music recordings, adding quick links to specific points in the video where each song started. Fig. 1 presents how Michael Jackson's *Thriller* album was made available using deep links in the Comments area.

*Lyrics videos* resembled still videos, but their visual content included songs' lyrics rolling with the music, similarly to karaoke

videos. *Embedded lyrics videos* were similar, but the lyrics were laid over the original *motion picture*, thereby augmenting the original classic music videos. In some overlays, lyrics appeared in two languages, most often in English and Spanish.

*Fan-illustrated* videos contained the largest amount of new material. In these videos, fans had recorded the video content anew by enacting it in fresh settings or in a novel medium (e.g., computer animation). Some of these videos looked very professional which made them difficult to distinguish from the official version. The distinctive feature of the user-enacted videos was their faithfulness (cf. User-illustrated subtype of Derivative videos) to the original classic music video and their lack of any embedded content. The audio track had been copied from the original version and the video respected the original video.

### 4.2.3. Derivative videos

Derivative videos were the most heterogeneous of all the primary music video types. These videos were inspired by the Classic music videos, but they included novel elements in their video, audio, or embedded content.

*Cover* versions were prominent in our sample, which was unsurprising given their central role in popular music overall. It is known that cover song versions can excel the original to the extent that they are perceived as "the" song.<sup>2</sup> In our sample, we also observed several YouTube channels and artists specializing in covering hit songs, as well as series of videos where cartoon characters performed the songs.

*Dance videos* showed dance performances set to the music. Audio tracks were usually copied from songs' original album versions. The main content in a dance video was the dance performance, not the music. This distinguished them from the user-appropriated videos.

*Parodies* were humorous interpretations of the original, classic music videos. The interpretation could focus, for example, on the clichéd or hedonistic worldview of the original video, the ways in which the artist performed the song, or other, more subtle aspects. To recognize the parody required a knowledgeable viewer, although parody videos usually had the word "parody" in their title, which also helped in categorizing them. Overall, this subtype was challenging to define precisely.

Our corpus did not feature misheard lyrics or literal videos – two known parody varieties. In a misheard lyrics video, embedded captions present an alternative way of hearing the lyrics, sometimes supported with purposely poorly drawn illustrations. In a variant of this format, the lyrics are misheard in a different language. Literal videos, in turn, are a relatively rare format where the video is copied from the original but the audio track is a complete remake. In the literal versions, the lyrics describe literally what is taking place in the video. A good example is the literal video of Bonnie Tyler's *Total Eclipse of the Heart*, which has been repeatedly removed from YouTube.

Finally, *user-illustrated* videos refer to all the videos in which the original audio is retained, but the video has been replaced with an unrelated or only marginally related visual content. In the corpus, we observed a few videos in which Minecraft computer game had been used to enact the original video's events, as well as couple of videos with video content from anime movies. Nine videos out of 400 remained unclassified after identifying the above-listed subtypes. Hence we created the *Other* subtype to group together the remaining videos. These included, for instance, remix and karaoke videos, which presented various combinations of novel music, video, or embedded content.

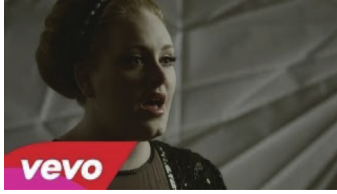
<sup>2</sup> See Yahoo Answer for the questions "Cover songs that are more famous than the original?" at <http://answers.yahoo.com/question/index?qid=20071110184601AAowzwX>.

**Primary types**

**Subtypes illustrated with the YouTube video thumbnail and video title.**  
 Visit <http://tinyurl.com/youtubemusicstudy> for live demonstration

**I Traditional**

**1. Classic music video**



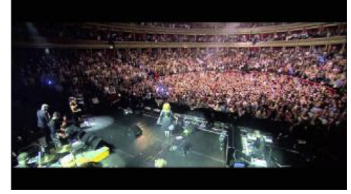
Adele - Rolling in the Deep

**2. Alternative version**



ADELE 'Rolling In The Deep' (Studio Footage)

**3. Live music**



Adele - Rolling in the deep (Live Royal Albert Hall)

**II User-appropriated**

**4. Still (cues: clear; audio; hd)**



Akon - Beautiful HD

**5. Lyrics (cues: lyrics)**



Britney Spears - I Wanna Go (Lyrics)

**6. Embedded lyrics**



Bruno Mars - Just The Way You Are Subtitulado Español Ingles

**7. Fan illustrated**



Rihanna - Diamonds

**III Derivative**

**8. Cover**



Justin Bieber - Baby , by 5 Year Old Skyler Wexler

**9. Dance**



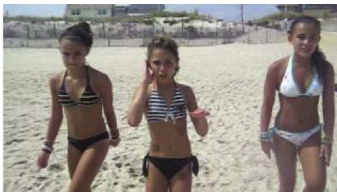
Chris Brown - Look At Me Now

**10. Parody**



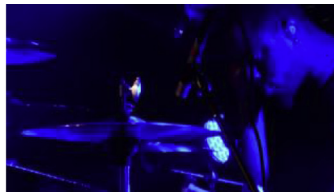
Shakira - Can't Remember to Forget You ft. Rihanna PARODY! Key of Awesome 83

**11. User-illustrated**



Party in the USA Music Video

**12. Other derivatives**



Rihanna -- Diamonds (Live Reggae Remix)

Fig. 2. YouTube's music video types (Roman numerals) and subtypes (Arabic numbers), illustrated with thumbnails and titles of example videos.



#### 4.2.4. Subtype frequencies and their ranks in YouTube's search results

Live music versions were the most numerous in our sample, representing 25% of all the videos ( $N = 400$ ; see Fig. 3). They were followed by classic music videos (12%), and lyrics videos (22%). The remaining subtypes represented each less than 10% of the sample. Among the derivative videos, covers and parodies were the most common (6% and 5%, respectively). Taken together, 38.3% of videos were user-appropriated, 37.0% traditional, and 24.8% derivatives. We also noted that 9% of the search results were either not music (e.g., YouTube channels, playlists, or stylized documentaries on how the original videos had been made) or represented a different song.

Calculation of average search rankings for each subtype's videos showed that YouTube gives priority to classic music videos. Their average rank was 6.3 on a scale from 1 to 20. One instance of classic videos was always the first in the results. Lyrics and Still videos appeared next in the search results (average ranks 10.1 and 10.4, respectively). All the other subtypes ranked equally (range 12.1–12.7), except for the Other derivatives, which had the poorest average ranking (16.4). A Kruskal–Wallis test indicated that the effect of video main type was statistically significant ( $\chi^2 = 71.445$ ,  $df = 10$ ,  $p < .001$ ).

#### 4.3. Discussion

Study II highlights two aspects of music on YouTube: (i) the remarkable richness of music video formats and (ii) the wealth of user-generated (both user-appropriated and derivative) content in search results for music. The majority of user-generated content was in harmony with original content, even if it was user-augmented. We believe that user-appropriated and traditional videos both support music listening function similarly and form an *extended music video* cluster of YouTube. The fact that the lyrics videos were the second most numerous subtype highlights the importance of user-generated content types in YouTube.

To account for the observed variation and heterogeneity in user-generated music video content, we introduced the concept of *user-appropriated content*. It grouped together various subtypes where original content had been reused to make the music (audio) accessible in YouTube. For user-appropriated videos, users had visually mashed up source materials or created new motion pictures that were in harmony with the artist. The term “appropriation” suggests that these contributions were not substantial enough to warrant original status, but were built upon the original. Their contribution augments the listening, but does not compete with it. This is interesting development of an unprecedented scale. Digital music is easily accessible material, readily malleable by freely available editing tools. When this potential reaches a global

audience, appropriation of music emerges as a much wider phenomenon than the previously studied appropriations such as low rider car tuning (Eglash, 2004) or home computer programming in the 1980s (Mackay & Gillespie, 1992; Turkle, 1984).

In our typology, the derivative videos seemed to provide different experiences by substantially departing from the original versions. Many of them represented the user-generated content for which YouTube initially became known for (Burgess & Green, 2009; Kim, 2012). Cover versions and parodies were the most visible, and some might even be classified as novel pieces. In our corpus consisting of 20 most relevant search results, the proportion of parody was 5%, exactly the same amount as in the “iPhone 3G” study by Blythe and Cairns (2009).

Our results were based on data that was selected from YouTube using its proprietary relevance metric. This method was adopted because it resembled what users would normally see. On the downside, using the relevance criterion also biased our data, by making the sampling procedure opaque and unreplicable in a strict sense. Nevertheless, even with a limited data sample and a proprietary metric, the variation in different user-generated content types was impressive. Analyzing user-created content with this extent of variation was a challenge. Although we did reach an excellent initial agreement, making clear-cut definitions for each subtype proved sometimes difficult. This was most evident in the analysis of user modifications that ranged from small changes (e.g., embedded captions) to major remakes (e.g., creating an animated fan video).

This particular problem is not unique to our study, but exemplifies the challenge of defining the extent that a video can change while still being considered a duplicate (see De Oliveira et al., 2010). Another surprise was that we did not encounter certain video subtypes in our sample whose existence we are aware of (e.g., bootlegs, misheard lyrics, and literal videos). Finally, we used terms such as “user-appropriated”, “user-illustrated”, and “user-generated” in the typology although our coding principles emphasized *content* over the author or publisher. The reason for the naming decision was that while the coding was content sensitive, our iterative process led to a coding scheme where each video was coded based on its difference to the song's classic video. With this coding scheme, content-level differences became related to the identities of the video creators (i.e., professional vs. user), but we noticed this relationship only after our typology was finished.

However, we do not claim that all “user-appropriated” video types are user-generated. In our first sample, we discovered three versions of the same song (Applause) in Lady Gaga's official YouTube channel: a still video, a lyrics video, and a classic music video. Few weeks later this channel also released a live version of the same video. This exemplifies the difficulties in labeling something as “user-generated.” YouTube's own role in this activity is that of an equalizer: it puts content producers and distributors on the same line as their consumers, maintaining some of the charm it initially promised (Burgess & Green, 2009) as an arena for user-generated content.

Overall, this study found that users contribute tremendously to making popular music available in YouTube and that the service promotes this content visibly. However, users do not just copy content, but they augment it. In our follow-up study, we will address how users engage with different types of videos.

#### 5. Study III: engagement differences in content genres and music video types

The previous studies addressed the popularity of music in YouTube (Study I) and the types of music videos that can be found (Study II), but they did not inform us how users interact with

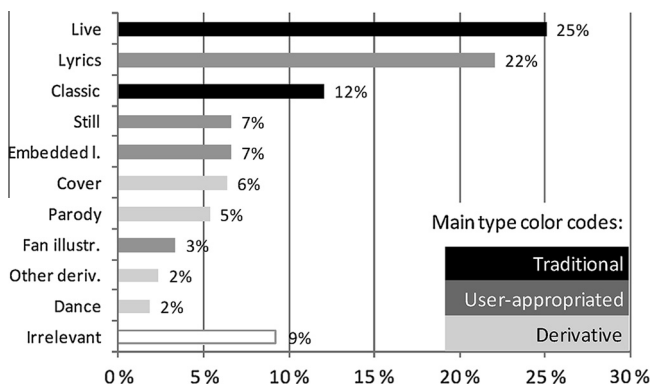


Fig. 3. Videos subtypes discovered within the first 20 search results for 20 popular music video titles on YouTube.

videos and whether music videos are any special in this regard. To address these questions, we analyzed video use on YouTube with quantitative metrics. We looked for differences in engagement, by which we refer to the three public traces of interacting with videos: viewing, commenting, and voting (see Section 2.1).

We conducted the study in two parts. In part (A) we will investigate if music videos differ from other YouTube video genres such as gaming or entertainment. In part (B) we will compare different music video subtypes. The part A is an extension to Study I with an inclusion of a variety of content from different genres, whereas the part B builds upon the typology presented in Study II.

Our approach was again exploratory, but in part (A) we expected to replicate the finding about relatively low commenting frequency for music videos (Thelwall et al., 2012). In part (B) we assumed that music videos under similar titles but different audio tracks would elicit different engagement patterns (De Oliveira et al., 2010).

As the following results show, music videos invited similar attention as other video genres, but in greater numbers. Within different types of videos, we found systematic differences between the video types in engagement. Especially responses to derivative videos stood out.

## 5.1. Study IIIA. Music and other video genre categories

### 5.1.1. Methods

To compare music videos against other genre categories, we gathered a dataset of 400 popular videos from four genre categories, 100 videos each: Music, Gaming, Pets and animals, and Entertainment. For each genre, we used ten search cues to retrieve ten videos from the YouTube search results.

To create the sample for Music, we selected ten popular artists (see search trends in Study I) as our search cues and restricted the search to the “Music” category. We included data only about those artists who had at least ten classic music videos within the first 50 search results (as returned by the API), when retrieved in the order of view count.

Because our sampling within the music genre was therefore popularity-based, we sought for a similar sampling also for the other video genre categories. Building on Study I, we investigated the lists of the most popular YouTube channels and used them to generate search cue lists, each list having ten cues.

For “Gaming” and “Pets and animals” genres we sampled ten videos from the search results from each of the ten search cues. In these genres the search was limited to the respective genre. For the “Entertainment” category, we made queries across all content categories, because videos were not consistently labeled for this category. The sampled items were found, in an order of descending frequency, from “Shows”, “Entertainment”, “Comedy”, “Film”, “Autos”, and “Nonprofit” categories.

In sampling of genres other than “Music”, we excluded derivative music videos from the search results despite their popularity. The cues contributing to data and the resulting video IDs of our data are available in Appendices A and B. Our sample focused on videos with a high number of views. This ensured that our sample also had an adequate number of comments and votes for statistical analysis, because these numbers are known to be correlated (Liikkanen, 2013). We then retrieved the statistics for all videos using the YouTube API for convenience and to retrieve all data in a short succession.

In addition to the numbers of views, comments, like votes, and dislike votes, we also computed three additional media engagement metrics to assess voting and commenting frequencies, and proportions of dislike votes relative to the numbers of views. The number of votes per thousand views (*VpkV*) and comments per thousand views (*CpkV*) denoted the frequencies of the activity while the

dislike proportion (*DisP*) measured the share of negative votes. These metrics allowed comparing engagement across videos that have a variable numbers of absolute views, votes, and comments, following the recent proposal (see, Liikkanen, 2013).

These preparations provided us with six variables (*Views*, *Votes*, *Comments*, *VpkV*, *CpkV*, and *DisP*) for analysis. Our task was to analyze how these metrics differ across the four genre categories. This analysis was carried out using a Multiple Analysis of Variance (MANOVA; SPSS 16) with content genre *Category* as initial independent categorical predictor and the six metrics as the dependent variables.

Before running MANOVA, we assessed the distributions of the dependent variables to detect multicollinearity and violations of normality. To mitigate multicollinearity we included only one variable from a group of correlated variables (see below). The normality violations were corrected by applying a logarithmic transformation to the dependent variables. In MANOVA, we used simple contrasts to compare Music category against the three other categories together. Additionally, we used non-parametric Kruskal–Wallis tests to verify the results.

### 5.1.2. Results

An analysis of pairwise correlations between the six dependent variables showed strong correlations between *Views* and *Comments* ( $r = .652, p < .001$ ), *Views* and *Votes* ( $r = .880, p < .001$ ) as well as *Comments* and *Votes* ( $r = .824, p < .001$ ). This indicated that the *Votes* and *Comments* were largely redundant and thus we only included *Views* in MANOVA. In addition, we found a moderate correlation between *VpkV* and *CpkV* ( $r = .545, p < .001$ ). The other correlations were below  $r = .3$  level. Thus the final set of dependent variables consisted of four metrics: *Views*, *CpkV*, *VpkV*, and *DisP*.

There were clear differences between the four content categories, as shown by the means for the dependents in Table 4. Most notably, the mean *Views* for Music was almost 13 times bigger than the other categories (191 million vs. 14.8 million). In addition, the Gaming category videos appeared to have higher commenting (*CpkV*) and voting (*VpkV*) frequencies than other categories, and the proportion of dislikes (*DisP*) for Pets and animals appeared to be particularly high. This suggested that the four content categories had different user engagement patterns.

We confirmed the observation about the means by the MANOVA results. The multivariate test showed that *Category* had a statistically significant effect on the dependent variables (Wilks'  $\lambda = .259, F(12, 1040.07) = 57.652, p < .001, \eta^2 = .362$ ). The univariate MANOVA tests further demonstrated a statistically significant influence of *Category* in all the four dependents (*Views*, *CpkV*, *VpkV*, *DisP*:  $p < .001$ ; *DisP*:  $p = .015$ ). This effect is illustrated in Fig. 4. While *Category* had a prominent effect on *Views* ( $\eta^2 = .654$ ), its effect was much smaller, while significant (on a level  $p < .05$ ), on voting (*VpkV*;  $\eta^2 = .171$ ), commenting (*CpkV*;  $\eta^2 = .206$ ) and dislike proportion (*DisP*;  $\eta^2 = .026$ ).

MANOVA contrasts confirmed that the difference between Music and other genres was related to greater *Views*. Music videos were also less frequently commented and voted than Gaming videos ( $p < .001$ ), at a level equal to the other genres. The differences in Dislike proportion suggested a greater dislike proportion for Pets and animals, although this main effect was not confirmed by non-parametric statistics.

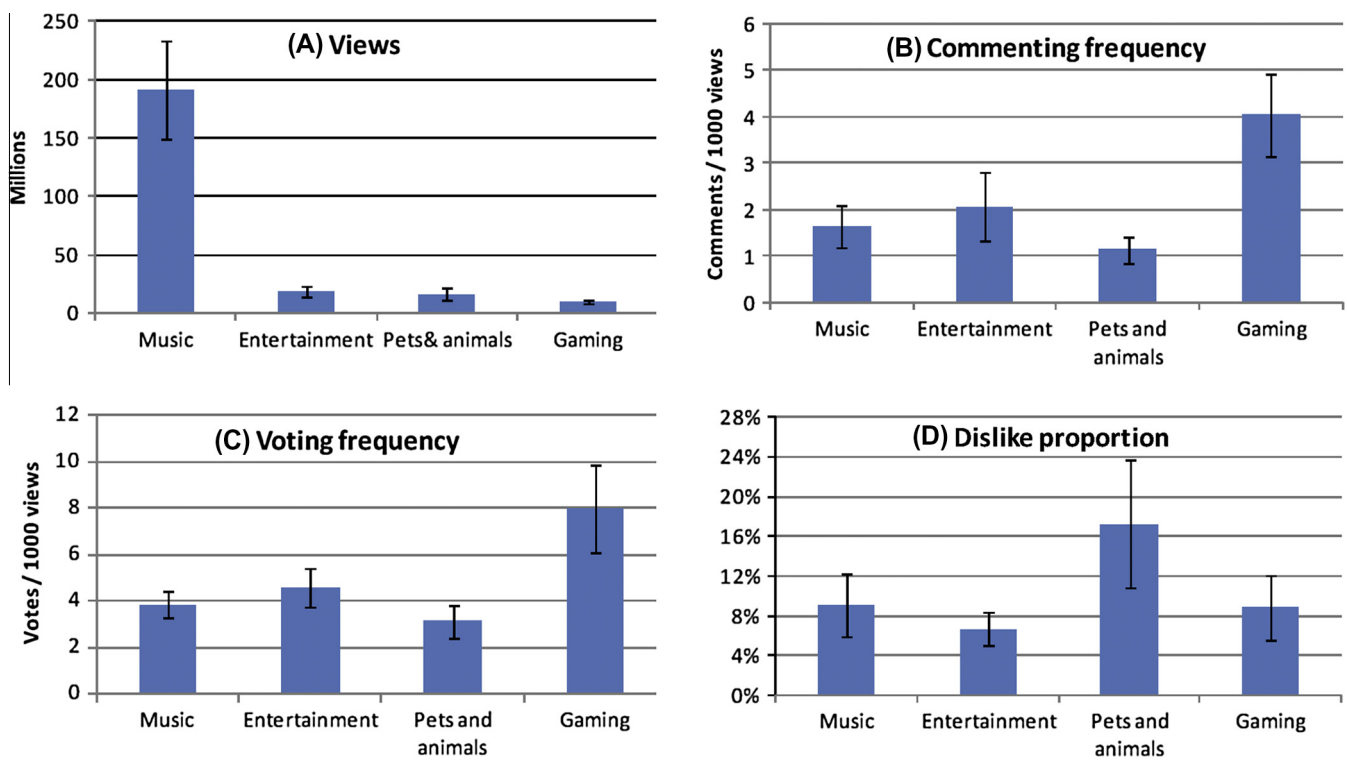
## 5.2. Study IIIB. Differences between different music video types

### 5.2.1. Methods

The latter part of Study III targeted music videos only. We selected five video (sub)types for this analysis: three from the extended music video cluster (classic, still, and lyrics videos) and two derivative types (parodies and covers). This enabled us to

**Table 4**  
Average measures of user engagement for four different video content genres.

	Music		Entertainment		Gaming		Pets and animals	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Views	191,286,418	150,597,872	18,626,175	14,575,496	9,811,575	6,866,867	15,956,924	17,720,947
Comments	391,362	978,464	35,761	42,412	39,826	59,432	16,820	28,265
Votes	718,040	680,201	80,321	81,373	73,488	86,549	45,727	71,509
Votes+	613,218	437,219	75,579	78,941	68,863	85,053	41,434	69,139
Votes−	104,822	380,117	4742	5873	4624	7040	4293	7295
CpkV	1.645	1.582	2.060	2.635	4.034	3.131	1.137	1.004
VpkV	3.871	2.081	4.591	2.877	8.004	6.738	3.128	2.562
DisP (%)	9.1	11.4	6.7	5.8	8.9	11.7	17.3	23.0



**Fig. 4.** Engagement across the four genres as measured by average views (A), commenting frequency (B), voting frequency (C), and dislike proportion (D). Error bars denote the 95% confidence interval.

explore several kinds of differences: For instance, do videos with identical audio tracks but different video content elicit different engagement patterns, and are there differences inside the extended music video cluster (see Section 4.3) and two derivative video types? The dependent measures were the same as in Study IIIA.

Our data was sampled from the Music category of YouTube. We first identified the most popular artists from the YouTube search keywords trends data (see Study I). We then used each artist's name as a YouTube search cue. We included the artist in our sample if we found at least three classic video titles with over 100 million views each. We hoped that this tactic would facilitate finding other, presumably rarer video versions. Of these highly popular videos, we picked at most ten titles from each artist for our sample. The resulting list of titles had 137 entries from 17 artists (see Appendix C).

We used YouTube's video search manually to find all the five video types for every title. We used the title of the song as a search term and appended it with additional search terms. For instance,

still videos were searched using additional keywords "audio", "clean", "HQ"; lyrics videos with "lyrics"; covers using "cover" and "version"; and parodies with "parody" if necessary. We evaluated the representativeness of each search result by the video's title, description, thumbnail image of the video, and actual video content. We discovered all the five video types for 108 titles (Appendix C).

We next retrieved the statistics for this sample of  $5 \times 108$  videos using YouTube API. The following criteria were used to filter the data. We required that all videos had at least 10,000 views and had their commenting enabled. We retained the video title in our sample only if this requirement was met on all the five video types of that title. With this criterion, the number of titles dropped to 84.

In data analysis we again relied on MANOVA. The dependent variables were the same three basic and three extended measures as we presented in Study IIIA. Now we had two independent variables, *Videotype* and *Artist*. The former referred to the five video types and the latter to the artists whose titles were sampled. Because we anticipated that the titles from the same artist would

give rise to similar user interactions, we considered *Videotype* as a repeated measure with five categorical values and *Artist* as a between-subjects categorical variable. Taking into consideration that we had multiple dependents, we consequently used a RM-MANOVA procedure. Similarly to Study IIIA, we inspected the data to identify normality violations and multicollinearity issues (see results).

As our interest lay in the possible differences within *Videotype*, we designed four a priori contrasts to identify them (see Fig. 5). Based on the prior research (De Oliveira et al., 2010), we hypothesized that the biggest differences would be found between the extended music video cluster and the derivative videos (C1).

### 5.2.2. Results

The basic descriptive statistics (Table 5) revealed a considerable variation in the dependent variables and notable differences between the video types. Direct measures (*Views*, *Comments*, and *Likes*) were much greater for classic videos than for the other types. Covers and parodies, on the other hand, invited more frequent commenting and voting (*CpkV* and *VpkV*) and they were more often disliked (*DisP*).

Before performing RM-MANOVA, we looked for multicollinearity issues. We found strong correlations between *Views* and *Votes* ( $r = .877, p < .001$ ), *Views* and *Comments* ( $r = .658, p < .001$ ), and with *Comments* and *Votes* ( $r = .835, p < .001$ ). Also, *CpkV* correlated mildly with *VpkV* ( $r = -.319, p < .001$ ) and *DisP* ( $r = .327, p < .001$ ). We subsequently excluded *Votes* and *Comments* from RM-MANOVA and assessed the normality for the remaining four dependents (for each type of video). Initially all dependents failed the Shapiro–Wilk normality test. However, after a base-10 logarithmic transformation of *VpkV*, *CpkV*, and *DisP*, 8 out of  $3 \times 5$  variables passed the test ( $p > .05$ ). The transformation did not fix the skewed distribution of *Views*, so consequently, we discarded *Views* from the main model and analyzed it using a separate RM-ANOVA model with *Videotype* as a factor.

To support interpretation of the analysis, we plotted the data into graphs shown in Fig. 6. Results from RM-ANOVA demonstrated that the view counts (*Views*) between different video types

(*Videotype*) were significantly and substantially different as expected ( $F(4,74.803) = 136.854, p < .001, \eta^2 = .880$ ). The post hoc tests confirmed that *Videotype*'s main effect (Fig. 6, panel A) was attributable to classic music videos, which had more views than any other types. A non-parametric Kruskal–Wallis test confirmed this finding. The differences in view counts between the other video types were non-significant.

The test for the dependents *CpkV*, *VpkV*, and *DisP* showed main effects on both independent variables; *Videotype* (Wilks'  $\lambda = .093, F(12.0,62.0) = 50.334, p < .001, \eta^2 = .907$ ) and *Artist* (Wilks'  $\lambda = .144, F(48.0,211.97) = 4.060, p < .001, \eta^2 = .476$ ). This means that the video types evoked different user engagement, also between different artists.

We also noticed a significant interaction effect of *Videotype* and *Artist* in our data (Wilks'  $\lambda = .011, F(192.0,624.67) = 1.933, p < .001, \eta^2 = .313$ ). This effect can be observed in Fig. 6 (panels B to D), where the lines representing different artists cross each other in many places. The interaction effect indicates that the responses to the videos of the same artist differed for different video types. This is easiest to observe in the case of derivative videos, in which the parody and cover versions may have totally different levels of engagement. For instance, Justin Bieber's classic music videos stand out in panel D as highly disliked, but the parodies or covers did not have similar dislike proportions.

The first contrast (C1) between the extended music cluster and the derivatives found statistically significant main and interaction effects in all three of the dependent variables (see Table 6). More specifically, derivative videos were more frequently commented and voted, and more disliked than corresponding videos of the extended music video cluster. The interaction effects (C1, *Videotype*  $\times$  *Artist* effects in Table 6) indicated that for some artists, commenting and voting did not change between the video types in the same way as could be predicted from the overall trend.

The second contrast (C2) tested the difference between classic music videos and the user-appropriated (still and lyrics) videos. This contrast displayed differences with respect to all three measures (Table 6). The classic videos were more frequently commented and voted on than the other types. However, the analysis also revealed an interaction effect of *Artist* and the *DisP*, meaning that for some artists, the general pattern of dislike proportion in our data (i.e., the greatest for the classic type, the smallest for lyrics) was reverse or non-existent (see Fig. 6, panel D).

The remaining contrasts (C3 and C4) did not reveal as many or big differences as the preceding ones. The differences between lyrics and still videos (C3) differed only by the degree of commenting frequency (*CpkV*), with still videos receiving comments more often. The fourth contrast (C4) addressed differences between the parody and cover versions. Parodies received votes less frequently, but their *DisP* was higher. An interaction effect indicated that there was considerable artist-borne variation between these two types of derivative videos.

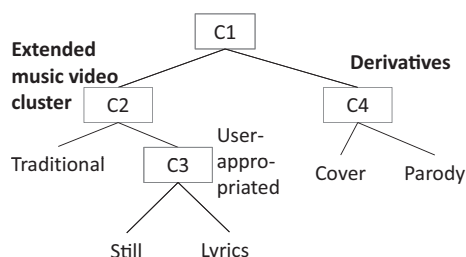


Fig. 5. Four designed contrasts (C1 to C4) for RM-MANOVA analysis.

Table 5

Average measures of user engagement for five different video subtypes ( $N = 84$  each).

Measure	Mean					Standard deviation				
	Classic	Lyrics	Still	Cover	Parody	Classic	Lyrics	Still	Cover	Parody
Views	215,554,389	18,096,798	5,072,229	9,133,647	5,736,085	150,254,933	24,229,626	10,335,995	14,953,529	10,437,044
Comments	294,915	12,820	3419	18,638	13,947	647,436	22,526	11,985	39,527	31,915
Votes	750,886	51,975	13,234	69,836	35,057	672,135	89,644	40,728	113,352	61,951
Votes+	649,997	49,489	12,119	64,840	27,899	441,172	85,916	36,503	105,926	48,313
Votes–	100,889	2486	1115	4996	7159	369,179	4523	5372	12,848	27,881
<i>CpkV</i>	1.19	0.48	0.67	2.14	2.95	1.14	0.45	0.55	1.6	4.28
<i>VpkV</i>	3.683	2.568	2.347	8.963	7.411	2.045	1.634	1.414	6.156	5.984
<i>DisP</i>	8.7	5.4	6.1	7.1	17.0	10.5	4.6	6.7	9.6	17.0

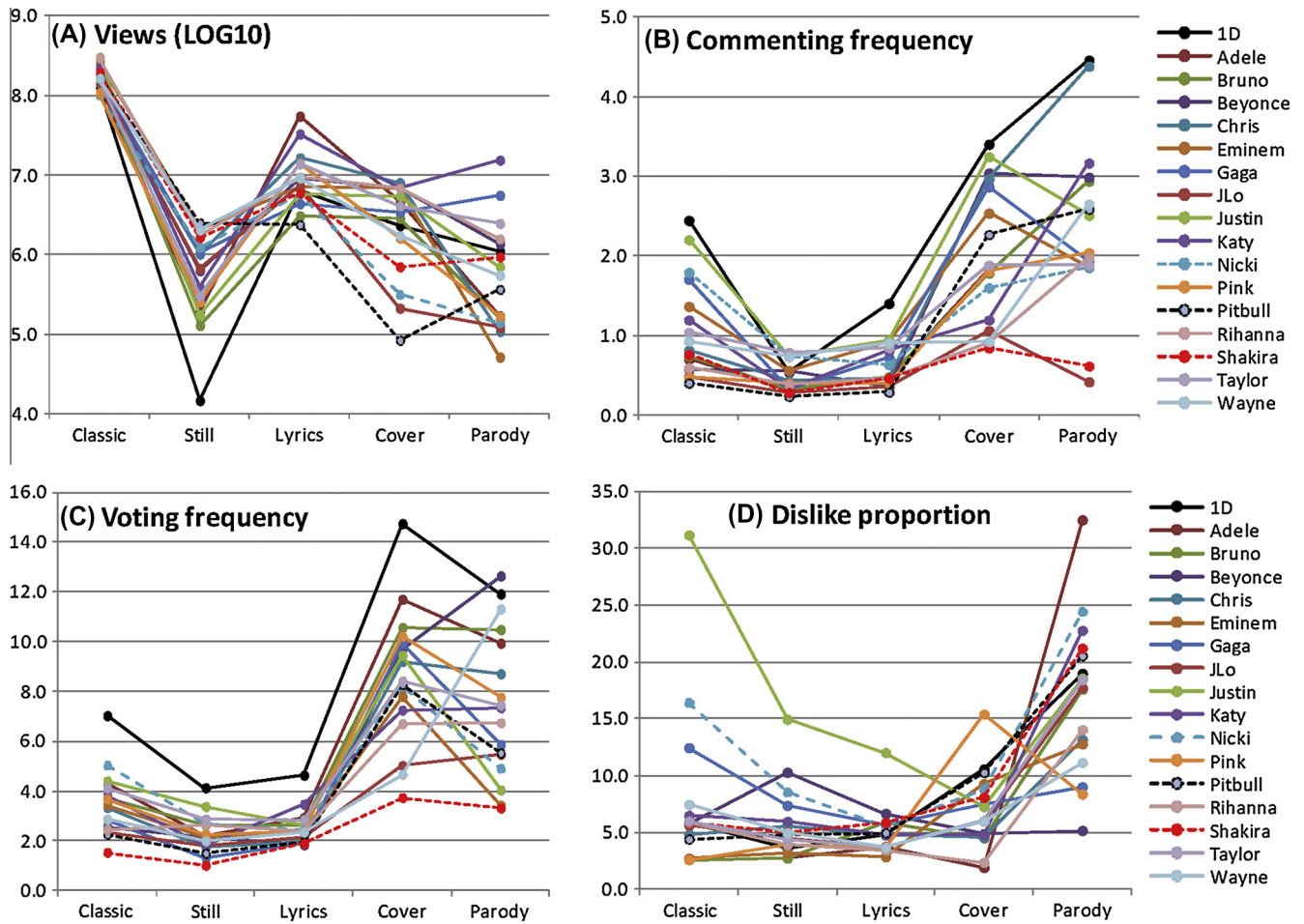


Fig. 6. Engagement measures of individual artists for each of the five video subtypes as measured by average views (A), commenting frequency (B), voting frequency (C), and dislike proportion (D).

Table 6  
The four RM-MANOVA contrasts for the three dependent measures.

Contrast	Terms	Measure	SS	df	MS	F	p	$\eta^2$
<i>Tests of within-subjects contrasts</i>								
C1	Videotype	VpkV	12.578	1	12.578	336.211	0.000	0.844
		CpkV	15.259	1	15.259	228.896	0.000	0.787
		DisP	1.118	1	1.118	16.742	0.000	0.213
	Videotype * Artist	VpkV	1.690	16	0.106	2.823	0.002	0.421
		CpkV	4.203	16	0.263	3.941	0.000	0.504
		DisP	2.377	16	0.149	2.226	0.013	0.365
C2	Videotype	VpkV	2.405	1	2.405	72.343	0.000	0.538
		CpkV	5.011	1	5.011	86.136	0.000	0.581
		DisP	0.708	1	0.708	16.433	0.000	0.210
	Videotype * Artist	VpkV	0.760	16	0.048	1.430	n.s.	0.270
		CpkV	1.180	16	0.074	1.268	n.s.	0.246
		DisP	3.174	16	0.198	4.602	0.000	0.543
C3	Videotype	VpkV	0.097	1	0.097	1.155	n.s.	0.018
		CpkV	0.756	1	0.756	11.381	0.001	0.155
		DisP	0.017	1	0.017	0.215	n.s.	0.003
	Videotype * Artist	VpkV	1.951	16	0.122	1.457	n.s.	0.273
		CpkV	1.094	16	0.068	1.029	n.s.	0.210
		DisP	0.836	16	0.052	0.656	n.s.	0.145
C4	Videotype	VpkV	0.921	1	0.921	7.396	0.008	0.107
		CpkV	0.225	1	0.225	1.678	n.s.	0.026
		DisP	10.968	1	10.968	37.036	0.000	0.374
	Videotype * Artist	VpkV	2.886	16	0.180	1.449	n.s.	0.272
		CpkV	5.456	16	0.341	2.537	0.005	0.396
		DisP	3.955	16	0.247	0.835	n.s.	0.177

### 5.3. Discussion

In this study, we found one major difference in engagement between music videos and videos of other genres and several differences between different types of music videos. Music videos of the traditional type had more views than videos from other genres, but otherwise engagement with them was similar to others (Study IIIA). Music videos stirred the most discussion, but only in absolute numbers. Because they attracted more viewers, they also received more votes and comments than other types. The frequencies of commenting and voting were the same as for other content genres, in contrast to the previous study (Thelwall et al., 2012). This finding is more interesting than the sheer overwhelming popularity of music videos we observed in Study I. It suggests that YouTube supports passive music listening whereas other genres, especially Gaming or Pets and animals, generate relatively more engagement.

The second part (Study IIIB) found many differences among different music video types. We found that derivative videos (covers and parodies) attracted the most frequent user engagement (contrast C1). This supports the argument that user-generated content evokes the most discussion (Burgess & Green, 2009). However, this argument needs updating, as our findings show that only certain types of user-generated content achieved this. Classic music videos received more user attention in terms of commenting and voting frequencies than the lyrics or still videos (C2). One reason for user-appropriated content's lower discussion level may be that when users feel a need to discuss about a song they are more likely to express their opinion in the context of the "authentic" classic video. A qualitative analysis of comments might show whether this is the case.

Several interaction effects between the video type and the artists also emerged in the analysis. This indicates two things. First, engagement with derivative videos cannot be predicted from the engagement with videos of the extended music video cluster. Second, despite the main effect of *Artist*, there seemed to be some stable effects attributable to a particular artist across the types. From Fig. 6 we observed that the engagement levels for artists were quite similar between the classic, lyrics, and still videos. We noted a "hater" bump for Justin Bieber's videos whereas One Direction's (1D) classic music videos enjoyed particularly high commenting and voting frequencies. This raises a question whether there are user segments that consume certain types of videos differently from others, leading to spurious patterns in engagement metrics. This possibility should be investigated in the future.

Some limitations about the data should be acknowledged. We sampled data among the most popular titles only. Regarding engagement, the utilized measures were quite shallow. Their detailed interpretation is difficult because YouTube does not disclose individual voters' identities, demographics or provide other disaggregated metrics. YouTube user accounts can be pseudonymous and therefore the aggregate measures based on comments and votes can be imprecise. But given that they are the *only* consistently available public statistics, we find their use justified for an exploratory study.

## 6. General discussion

This paper has explored the popular forms of music in the YouTube video service. By the measures of Study I, music proved to be the most popular content type in YouTube. This firmly establishes the significance of our topic among the multitude of activities humans perform with mobile and desktop devices. Study II proposed that music videos can be divided into three main types: traditional, user-appropriated, and derivative music videos. These

further divide into several subtypes, each of which was defined with unique combinations of audio, video, and embedded information. Study III demonstrated how the YouTube audience engages differently with the different content genres and music video types.

Based on these findings, we contend that user contributions to YouTube's music video culture consist of augmenting and replicating original audio content; neither merely creating user-copied content (Ding et al., 2011) nor only redacting or quoting professional content (Burgess & Green, 2009). While user-augmentation and replication may lead to deterioration and changes in content quality (see, Plazak, 2012), the resulting videos seem to find their audience, given their overall popularity and prominent place of user-uploaded music content in the YouTube search results.

The present study has given a fresh perspective to "user-generated" content in online cultures. Foremost we proposed "user appropriated" as a new main type of user-generated videos, which lies between user-copied and user-created videos. This is based on the observation that YouTube users have collectively developed new content formats (e.g., still videos) and expanded the old ones (e.g., lyrics videos). In this regard, the situation seems different from what Burgess and Green (2009) described as user-generated, meaning that users would be actively publishing their own, authentic content. We find Kruitbosch and Nack's (2008) statement that the "most of the popular content on YouTube was professionally generated" (p. 7) closer to reality.

Although professionally created content from major record labels is the locus of users' attention, our studies prove that they present only a tip of the iceberg. In fact, we believe that the professionally produced popular music content becomes overwhelmed by user-appropriated content in YouTube so that the latter is collectively more popular than the traditional video (see the following subsection). From the perspective of appropriation (as in social studies of technology), YouTube music provides a fresh and hugely widespread example of how users appropriate a service by both repurposing and taking control over the content production.

We see an interesting parallel between YouTube and the C-cassette which was a widely used peer-to-peer music distribution medium from 1970s to 1990s. They share similar features, such as ubiquitous access, user-copied content, and variable technical quality. However, while there are shared characteristics, the use of music and its distribution have radically changed with YouTube. For example, our research demonstrates the popularity of user-appropriated music video types, whose distribution would not have been feasible in the past corporate-dominated media space. But now, on YouTube, user-generated videos have at least theoretically an equal chance to gain world-wide audiences and introduce new content, creators, and publishers to public awareness (see, Burgess & Green, 2009). This is especially important for distributing information on subjects and in regions of political controversy, although it reflects on YouTube music as well. For music, this means new career opportunities for artists to find their audience across the world — as long as they can capture the attention with the dynamic YouTube audience.

### 6.1. Halo effect

Our second study showed that user-appropriated videos have a prominent place in YouTube's search results. This raises a question whether the different music videos reinforce each other's popularity, creating what we call a *halo effect* — that a popular video may share its audience collaterally with similar contents because they appear next to it in search results and suggested content, thereby increasing their views. Because the classic music video is usually the first to be published on YouTube, and because YouTube gives prominence to traditional music videos uploaded by official

sources, the benefiting parties are the creators of user-appropriated and derivative music videos.

In addition to our findings on the prominence of user-appropriated videos, there are also two other signs of the halo effect. First, the Search and Featured content functions in YouTube (see Section 2.1) are known to drive the video views (Broxton et al., 2013; Cunningham & Nichols, 2008; Liikkanen, 2014; Zhou et al., 2010). They also promote user-generated videos by displaying them next to the original content with an equal status.

Second, it has been recorded that “user-generated” YouTube content produces more revenues for the artists than their original videos (IFPI, 2014). This supports the halo effect hypothesis, because ContentID mechanism of YouTube enables copyright holders to receive royalties also from user-appropriated content. The finding on revenues suggests that user-appropriated videos are enjoying a popularity that together exceeds the popularity of the original classic videos.

The bond of professional and user-generated videos seems reciprocal in the sense that for every original YouTube music video released by a popular artist, hundreds of user-appropriated videos are created by users. Record labels have undoubtedly observed the benefits of this activity and are using these user-appropriated music video formats (lyrics and still videos) to make their own “user style” YouTube releases. Apparently these new formats which would have been ill-fit to the MTV era music video distribution, lacking motion picture, work fine with YouTube audiences. This means that there is no need for the major players to publish under pseudonyms (see, Hartley, 2008).

The halo effect might be one of the reasons for the wealth of user-generated music content in YouTube. It allows users to seize the opportunity and publish content that receives a share of free publicity. We believe they are usually not after monetary gain, although we perceived occasions where users had uploaded modified user-appropriated content, possibly with an attempt to avoid the detection of copyright infringement and to make money. Qualitative studies would reveal the different motives – monetary, vanity, or others – behind the creation of user-appropriated content.

## 6.2. User engagement

Music videos stand out from other YouTube content mainly by their popularity. In Study I we found that the most popular music videos have hundreds of millions of views while the most popular videos in other categories receive less than a tenth of that. While music videos stand out in viewing-based measures, Study IIIA showed that in other respects their consumption was no different. The engagement measures that we used (i.e., *VpkV*, *CpkV*, and *DisP*) showed that for a typical popular music video, it takes hundreds of views to accumulate one vote and even more views to receive a comment.

However, Study IIIB demonstrated that users comment and vote on derivative video types such as parodies and covers more frequently than with the user-appropriated types. It seems credible that parodies are more controversial and provocative, thus sparking many opinions, maybe even flaming. Negative votes were generally speaking infrequent in all video types (under 10% in all votes), but almost doubled for parodies and were consistently higher for some artists. We believe this reflects a “hater” phenomenon that is prominent with certain artists. For instance, Justin Bieber is known for loyal fans, called Beliebers, but he also faces a named opposition, the non-Beliebers (see [http://en.wikipedia.org/wiki/Justin\\_Bieber](http://en.wikipedia.org/wiki/Justin_Bieber)).

Previous research has identified a similar phenomenon in YouTube commenting. Moor et al. (2010) used Social Learning Theory to explain flaming in YouTube. They argued that if flaming appears as a norm in YouTube commenting, it will consequentially

promote further flaming. It seems uncertain whether this phenomenon can be generalized from comments to voting because of the different underlying mechanisms. In Study III, we observed only mild correlations between commenting and voting behaviors, indicating that at least on an aggregate level these reactions seem unrelated. High dislike proportion did not imply high commenting frequency. Overall, the elevated dislike proportions for some artists' videos raises the question of what do voters vote for. It suggests that YouTube voting might signify two different things: the viewer's disapproval of the video content (i.e., the ordinary interpretation of a vote) or the viewer's general negative orientation toward the artist or the publisher.

One surprising finding was that users engage (vote and comment) with still videos almost similarly as they do with other music videos. Although still videos were fewer in number and had fewer views, their audience was still calculated in millions. This shows that music remains interesting regardless of the presence of motion picture as an accompanying medium. Therefore music videos seem to be an audio-first format, in contrast to the majority of YouTube videos (De Oliveira et al., 2010). Users' interest in making the music (and only music) accessible through YouTube might explain why they are not investing effort in illustration of their videos, even if this would be quite easy with tools such as Adobe Voice (see also Hietanen, Salovaara, Athukorala, & Liu, 2012). One may speculate that still videos are well-suited for background listening, or that the still videos are convenient for publishing audio content which never had motion picture.

## 6.3. Limitations and future work

User behavior and technology decisions evolve as the services change and new ones become available. Our work is but one step in exploring the present and future of music videos on YouTube. More research efforts are needed as the digital service landscape changes and the policies and the interfaces of YouTube evolve. By the time this paper is published, YouTube has already taken a step to corroborate their music offerings through a music streaming subscription service known as YouTube Music Key (<https://www.youtube.com/musickey>). It will likely influence the content and interaction patterns this study has described as its features (e.g., offline access) promote even further audio-first interaction.

Our work involves some disclaimers. We explored YouTube by focusing on the most popular music content, as measured by the number of views. There are still hundreds of millions of music videos in YouTube that we did not consider. Given the relative lack of previous work and the considerable potential for directing research, we consider this as an important exploratory pilot study, providing inspiration for future work.

We made some assumptions in our work. For instance, in creating the typology in Study II, we disregarded the distribution channel's identity in defining the video subtypes. This factor should be investigated for its impact on user engagement. User-appropriated content creators should also be studied to discover who they are and what motivates them. The picture of content consumers is also imprecise. Do users prefer certain video types over others, do they use YouTube for music listening only, and why do they comment or vote?

Our video typology could also be considered as a set of hypotheses for studying how users react to different types of music videos. For instance, are still videos regarded as more authentic than lyrics videos? Also, the video types could be approached by considering the different functions they may serve, for instance, whether user-created live videos are used primarily as memorabilia (cf. Vihavainen, Mate, Liikkanen, & Curcio, 2012) or as audio-first recordings. Further research should also look at the nature of YouTube music listening experience, such as the sound and video

quality in YouTube and their interaction. Answering to these questions requires a combination of qualitative and experimental methods.

Although the typology and the interaction patterns are based on YouTube, we believe that these findings could be generalized. The same typology and interaction patterns may represent the Internet's music-related remix culture (Lessig, 2008) in the Internet more generally.

The findings therefore offer new material for the research on the relationships between the producers and consumers of digital media. YouTube, by presenting professional content and user-created content side by side, is an example of constant tension and negation of boundaries between traditional professionals and outsiders. Although the user-generated videos usually produce royalties for the original music's copyright holders, the content still infringes copyrights. The professional producers may wish to sustain the fan base and its creativity in YouTube but to exercise some control over the user content, as demonstrated by the frequent removals of infringing content. This tension offers opportunities for more research both from the consumer culture (Burgess & Green, 2009) and media industry (Hull, Hutchison, & Strasser, 2011; Peitz & Waelbroeck, 2005) points of view. Our findings on different interaction patterns across music video types may provide a structure for more detailed analyses on producer–consumer relationships within and across video types.

We have also suggested that there is a halo effect influencing YouTube music videos — a tentative hypothesis on the popularity spreading from the highly viewed content to the neighboring content in the service. Testing the effect in detail would require a dataset that contains music videos of varying view counts, as opposed to the very top used in this study. These data would allow for an analysis of correlations between view counts and the extent of user-generated versions. Specifically, one should look for higher view counts among those songs that have relatively more user-appropriated or derivative versions than the average. Another option would be to gather a longitudinal dataset that would allow researchers to assess which video types attract users to view more content.

Finally, there is a big question of regional differences in video types and audience engagement. We surveyed content foremost produced in North America for the global market. Apart from a few Spanish exceptions, this content was in English and represented the so-called Western pop music culture. But we are aware of strong national music cultures present in YouTube in Eastern Europe, Turkey, Thailand, South America, and Finland, for instance. Cross-cultural replication of the study 2 might be a natural first step in answering this question.

## 7. Conclusion

YouTube opens up a world of marvels when it comes to accessing music. It presents a new step in the line technological of development of recorded music distribution that started with the phonograph. This latest development of medium is paralleled by a development of musical content. YouTube offers professionally-generated content along with user-generated, often user-appropriated content. Our study showed that the user interactions with these video types are significantly different from each other. For example, traditional videos receive more views but derivative videos invite more active viewer participation through commenting and voting. If music videos are compared to other content genres on a higher level, such differences are not observable and the high view count appears as the sole unique characteristic of music videos. This paper's typology revealed the heterogeneity in online music videos and that this typology helped us to find user behaviors that otherwise would have remained hidden.

Digital music listening continues to change rapidly. Increasing understanding of this central entertainment function of information technology requires firm classifications on which the observations collected at different times can be anchored to. Through comparisons between and within content genres, we created a typology of music video types. We hope that this paper will provide analytical tools for analyzing and understanding Internet users' online music interaction in future, and a data point to compare current music behavior with the past and future.

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## Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.chb.2015.01.067>.

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