YouthTube: Youth Video Authorship on YouTube and Vine

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ABSTRACT

What kinds of content do children and teenagers author and share on public video platforms? We approached this question through a qualitative directed content analysis of over 250 youth-authored videos filtered by crowdworkers from public videos on YouTube and Vine. We found differences between YouTube and Vine platforms in terms of the age of the youth authors, the type of collaborations witnessed in the videos, and the significantly greater amount of violent, sexual, and obscene content on Vine. We also highlight possible differences in how adults and youths approach online video sharing. Specifically, we consider that adults may view online video as an **archive** to keep precious memories of everyday life with their family, friends, and pets, humorous moments, and special events, while children and teenagers treat online video as a **stage** to perform, tell stories, and express their opinions and identities in a performative way.

Author Keywords

Child; teenager; authorship; online video; YouTube; Vine.

ACM Classification Keywords

H.5.1. Information interfaces and presentation (e.g., HCI): Multimedia Information Systems: *Video*.

INTRODUCTION

In 2015, Frontline released "Generation Like," highlighting how social media has changed the way children and teenagers connect and enact identity, which has in turn changed who creates the content that influences the opinions and practices of this generation [42]. Whereas in the past, youth-targeted content was authored primarily by media giants such as Disney's *The Mickey Mouse Club* and MTV, the new media empire increasingly includes content authored and shared by other children and teenagers [43,44]. What does youth video authorship and sharing look like in a generation where Internet fame may only be a single viral post away? We contribute to answering this question by investigating youth video authorship online, in the hope of informing the design of platforms that can foster creativity and collaboration around online video content while still protecting online safety and privacy. Additionally, this work contributes to an important thread within CSCW on understanding how teenagers and young adults develop unique practices with social media, including videochat [9] and instant messaging [17]. Revealing the differences between the practices of teenagers and adults can highlight both generational and developmental differences in the use and attitudes to common social media technologies.

We use an expanded definition of *video author* [10], as one having an active role in creating or contributing to the creation of original video content. Perhaps it is more helpful to specify who is not an author based on our definition: one who simply reposts existing content without change (e.g., capturing a scene from a movie) or one who is unaware that the video is being created (e.g., a toddler captured in the park in natural activity is generally not taking an active role in the creation of the video). We know a great deal about how adults author online video; for example, we know that 18% of adults post original content on online platforms, such as YouTube and Vimeo [30]. We know that teenagers are comfortable using video as a communications medium to "hang out" [9]. We also know that teenagers are frequently active participants in online communities and social networking sites like Facebook, Snapchat, and Vine [24]. However, we know very little about how children and teenagers author and share video content, despite the leading role that authors as young as seven take in some of these communities [43]. In this paper we aim to address this gap by answering a single research question: **What kinds of content do children and teenagers author and share on public video platforms?**

We answer this question by examining the videos children and teenagers make publicly available on YouTube and Vine as primary sources of evidence. Through this content analysis process, we contribute not only a novel understanding of youth video authorship practices, but also articulate an effective approach to filtering relevant content authored by a particular population of interest.

We begin this paper with a brief overview of video sharing platforms, describing why we chose to focus this investigation on YouTube and Vine. We describe the related work in this domain to help articulate our contributions both in terms of the findings of our study and the particular approach we take to filtering relevant content. We briefly describe a situating study looking at parents' understanding of

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their children's online video sharing practices, before discussing the methods and findings of our content analysis of youth-authored online video. We end with a discussion highlighting unique aspects of Vine as a platform, a comparison of the differences in use of video platforms between youths and adults, and a reflection on our methodological approach.

VIDEO SHARING PLATFORMS

There are many platforms and communities that support video sharing:

- **YouTube** is the largest community for sharing video content online. It has no genre constraints or time limits and provides billions of public, searchable videos.
- **Twitch** hosts a large collection of public videos focused on live-streaming of video games including game tournaments, screencasts, and play-throughs.
- **Vine** is a public video-sharing platform owned and operated by Twitter and best known for its 6-second time limit.
- **Instagram** began as a photo-sharing platform but has recently expanded to support short (3-15 second) video shares.
- **Snapchat** is an app that provides mobile picture and video sharing with a particular feature of content "expiring" after a certain time period. Public sharing is enabled through the story feature, which displays a shared video or photo for only 24 hours.
- **Facebook** is a general-purpose social networking site. It allows sharing videos and photos with different privacy settings.

While all of these are popular with children and teenagers [24], we chose to focus on YouTube and Vine as the two most popular platforms where public video sharing is the primary purpose.

RELATED WORK

Our work is situated in previous investigations of public video sharing platforms and understanding and parenting online practices of teenagers, but we contribute a novel understanding of youth-video authorship practices. While our efforts are methodologically influenced by work that filters and analyzes videos of specific populations of interest, we also contribute a new approach to filtering relevant content.

Understanding Public Video Sharing Platforms

We are not the first to investigate public video sharing platforms like YouTube and Vine. For example, Pew Research Internet Project conducted a large-scale survey of online video in 2013 to find that 18% of adult users author videos and post them online [30]. From this large scale study, we know that adult authors most commonly post videos of family and friends doing everyday things (58% of the authors), themselves or others doing funny things (56%), and events they attend (54%) [30]. Ding et al. examined YouTube authorship, finding that while YouTube hosts a massive number of contributors, 63% of the most popular uploaders were primarily sharing user-copied (rather than user-authored) content [11]. Looking more closely at specific user-authored content, Biel and Gatica-Perez' investigation examined specific media characteristics of user vlogs and how they correlate with popularity [8]. Farnham and Churchill suggest that people maintain faceted lives online, choosing identity presentation based on the affordances of various technologies [12]. Finally, Rotman et al. enhanced our understanding of what motivates people to contribute content to YouTube through a mixed-method investigation of perceived community and sense of belonging on this platform [33]. Despite the fact that we know that age affects authorship in online video communities [30], none of these studies examined youth authorship on video sharing platforms.

Vine has been investigated considerably less than YouTube, though we know that a quarter of teenagers have Vine accounts [24]. Zhang et al. quantitatively examined repost traces of over 50,000 video clips and 1,000,000 user profiles on Vine, showing that this platform is distinct from others in several ways, such as encouraging unique batch viewing practices and exhibiting an unusually strong skew in the distribution of views, with the top 5% video clips accounting for more than 99% of all reposts [41]. However, neither of the above investigations examined video post content. Although Vine has been identified as an important part of the research agenda for understanding video interaction [23], we are one of the first to examine the content of the videos shared through this platform.

Understanding Parenting of Children's and Teenagers' Online Practices

Studies of children's and teenagers' use of social networking and online sharing platforms have largely focused on parenting and privacy practices online. For example, through over 100 semi-structured interviews with parents, we know that that many parents carefully consider, curate, and shape their children's online presentation [4]. Another paper in this series of studies has also identified a number of rules and practices that parents have for limiting their children's online presence [40]. However, these studies may have been limited in their findings by not including the voices of the children or teenagers, since other studies have pointed out that parents generally have fairly limited insight of their children's online practices [35]. Other qualitative interview work in this space included teenagers in the conversation about parenting and online privacy practices, finding that parents' and teenagers' practices and values frequently did not coincide, but were moderated by the moral development level of the child [39]. Large scale investigations, like Pew Internet Research surveys with both parents and children around privacy practices, found that going outside parental guidelines was not always negative, as adolescent risk taking online can be related to the development of coping mechanisms and resilience to negative outcomes [32,37,38]. From this body of work it is clear that children's and teenagers' online sharing activities are important both for parenting practices and in the process of growing up online; however, parents' and children's perceptions and practices frequently differ. While parents are concerned with online safety across emotional, physical, and social dimensions, the challenge is to create spaces that still allow the flexibility for children and teenagers to learn their own risk management strategies, and to negotiate social conflict in positive ways [22,32].

Inspired by this work with parents, we began our investigation with a situating study of parenting practices around youth video authorship. Ultimately, however, we found that the primary source of videos authored by youths themselves was a richer source of evidence about their online video creation practices.

Using YouTube as a Primary Data Source

We are not the first researchers to leverage public video sharing platforms as a primary source of data in understanding a specific population. For example, Anthony et al. gathered and analyzed videos of technology use by people with motor impairments by combining disability- and technology-related search terms [5]. More recently, a similar approach of combining demographic- and technology-related search terms was taken by Hourcade et al. to understand infants' and toddlers' use of tablet devices [19]. This approach has also been applied to the health domain, for example by Liu et al. who analyzed health video blogs on YouTube by searching for vlogs relating to specific health conditions (i.e., diabetes, HIV, cancer) [26]. While we were inspired by these techniques, our initial attempts to reproduce them showed that a keyword-based search would not work well for identifying youth-authored videos for analysis, since authorship information was generally not included in the title, keywords, or description of the video, and almost no people populate their demographic information in the bio. One of the contributions of this work is articulating an alternative process for filtering relevant video data when available search terms do not generate an adequate data set.

Approaches to Understanding Specific Populations' Use of Public Video Platforms

Previous investigations have taken four approaches to understand specific populations' use of public video platforms. We go through these below to articulate how our approach builds on and contributes an alternative to previous work.

One approach to understanding a specific population's use of public video platforms is to follow a specific group of participants in a target demographic and observe their use (if any). For example, Sayago et al. followed a group of 32 elderly study participants to understand their technology use, including whether, when, and how they used YouTube [34]. Unfortunately, this may not work for sparse examples of use, for example, if only a few members of the population of interest author video content.

Another approach to understanding a specific population is identifying and analyzing media that may be of special interest to that population. For example, Asselin et al. investigate student discussions around online educational videos [6], focusing on educational videos and channels identified by soliciting the advice of educators in the field. However, when the relevant types and topics of content are unknown (or are in fact the research question, as here), this method does not work.

A third approach is large-scale survey sampling of the target population. For example, the Pew Research Center report on Teens, Social Media, & Technology surveyed over one thousand teenagers to find that 52% of them reported using Instagram, 41% used Snapchat, and 24% used Vine [24]. However, this does not support a rich analysis of content and practices in the use of these platforms. For example, we do not know *how* each of these is used, such as whether teenagers were authoring content on these platforms and what type of content was being authored and shared.

Lastly, this work was influenced by the automatic content filtering approach to identifying a relevant population, proposed by Jang et al. in their analysis of teenagers' use of Instagram [21]. To compare the Instagram accounts of adults and teenagers, they searched through text descriptions of age for cases when somebody stated age in their bio and utilized the age analysis characteristics of the Face++ face recognition API on the profile photos. However, they found that the API struggled with detecting teenagers and the data required some by-hand validation. This is an excellent example of a situation where human intelligence is capable of combining diverse evidence (e.g., photo, video, voice, text) to make a more coherent determination of a person's age than would be possible by a machine. Inspired by this idea, our work contributes a crowdsourcing method for identifying and filtering relevant youth-authored content on public video sharing platforms.

SITUATING PILOT STUDY: PARENTS' PERCEPTIONS OF YOUTH ONLINE VIDEO AUTHORSHIP

Similar to other studies in this domain (e.g., [40]), we began our work by reaching out to parent for useful insights about family rules regarding their children's online video practices. To do so, we conducted a situating pilot study through an online questionnaire of parents. We present this study here in the interest of sharing an approach that *didn't* work with the community, as revealing unsuccessful approaches frequently offers value to other researchers.

Parent Questionnaire Methods

Our online questionnaire targeted parental attitudes and beliefs about their own children's video-authoring practices. We reached out to parents of children between the ages of 7 and 17 who post videos online. We gathered basic demographic information and asked parents how frequently their children make videos, the technology and sites that children use in the process of creating and sharing the videos, and their family rules and practices around children's video sharing. We promoted the online questionnaire through a paid Google Adwords advertisement, a paid targeted Facebook promotion campaign, and through social media and word-of-mouth by the research team. The respondents were offered a chance to enter a drawing for a retail gift card in exchange for their completed questionnaire. A total of 54 responses were recorded though only 18 were validated as relevant for this study (i.e., responses where parents knew about and were able to articulate their children's video-authoring practices). Due to this small number of relevant responses, we focus on the overall insights and qualitative findings from this process.

Parent Questionnaire Results

When asked about family rules around video-authorship, most parents (61%) responded that their children controlled their video-authorship appropriately on their own, suggesting little need for direct supervision or oversight. However, in discussing specific rules or practices, parents frequently suggested that they did have rules. For example, 72% of parents reported allowing their child to show their videos only to family and known friends, though they also reported that these videos were shared or uploaded via YouTube or Snapchat. For videos that were allowed to be public, there seemed to be a common rule of allowing the child to use their voice in a video but not allowing a child to show their own face or the face of other family members or family environments in the videos. A few respondents mentioned that they do not monitor their children's video sharing habits, but do give them behavioural guidelines. For example, two participants described these rules as:

> *No swear words, nudity, etc. They must follow what I consider to be normal human behaviour as if they were in public and everybody can see them ... I keep a fairly strict set of rules for my daughters.*

> *Act appropriately—meaning nothing violent, no bad language, etc. Basically, the same way they are expected to act at home or in class. Also, no identifiable information in the videos, like their names.*

However, several parents also reported catching their children posting videos that violated the guidelines set for them:

> *Along with his brother and cousin, my son recorded a screencast of Sid the Science kid with them doing rude voice-overs in the style of YouTube Poops. Then he uploaded it with rude language in subtitles ... When I discovered this video I asked him to remove it and [not] create or upload videos like it, with "inappropriate" language or behaviour.*

> *[The video] was a "let's play" of a game that I didn't want him playing because I felt it was too violent.*

These comments suggest that there may be interesting video-authorship practices happening outside of parental supervision.

Parent Questionnaire Discussion

Though this research team has significant experience working with parents and families, we found that it was unusually difficult to recruit for this project. We found that many parents were unaware of or unwilling to discuss their children's online video practices. Though we asked questions about specific content posted, few parents opted to specify what their children posted online or discuss examples of their children's video.

The results from this questionnaire led us to doubt whether parents were entirely aware of their children's online video practices. For example, while previous studies show that a quarter of teenagers use Vine [24], none of the parents in the questionnaire mentioned this platform. Additionally, many parents mentioned comprehensive rules regarding their children's video sharing such as not showing faces, inappropriate dress, and inappropriate language. In contrast, even a casual examination of video sharing services reveals many videos do not follow these rules. Indeed, this is consistent with previous work that shows that parents may have limited insight into the children's online experiences [35]. Our main take-away from this situating study was that asking parents was not a good approach for identifying and understanding youth video authorship practices. While the situating study was helpful in revealing some family rules that some families have around video sharing, to address our primary research question about the content of shared videos we turned to publicly shared video content as a primary source of evidence on youth-authored video.

CONTENT ANALYSIS STUDY: YOUTH AUTHORSHIP ON YOUTUBE AND VINE

The preliminary study with parents left us with more questions than answers about youth online video practices, so we decided to examine publicly-shared videos as the primary source of evidence for content created and shared by children and teenagers. Below, we describe the process of identifying youth-authored video and conducting the content analysis, as well as our findings from this process.

Identifying Youth-Authored Video

We identified a set of youth-authored videos by using Amazon Mechanical Turk to categorize the evident authorship of thousands of recently shared videos from YouTube and Vine.

Gathering the Initial Video Set

To identify the most promising sources for the video data set, we gathered an initial set of 50 most recently posted (as collected in August 2014) public videos per YouTube category and 100 most recent Vine videos shared on Twitter. Recent videos were chosen as the most equivalent way of getting a "random" set of videos from YouTube and Vine. While the YouTube API provides no way to get "random" videos, we can get those posted within a certain time period. We chose "most recent" because Vine does not provide an API, so we could only collect recently shared videos by setting up an hourly script. Three researchers looked through these videos, tagging those that were likely to have been posted by a minor (e.g., child on camera, child's voice, etc.). Using this approach, we created initial filtering mechanisms such as excluding YouTube categories that did not feature at least one child video out of the 50 videos viewed (e.g., "Gaming" was included, "News & Politics" was not). This piloting process also helped us develop intuitions and conventions for structuring the Amazon Mechanical Turk HIT to scale up the filtering process (described in the next section).

Once we developed these categories, we used the YouTube API and Twitter API to collect a data set of about 5000 recently posted videos from YouTube and another 5000 of unique recently shared videos from Vine. We collected a larger set of videos than we anticipated we would need, to account for videos being removed and to be able to expand our analysis as needed. This proved warranted as we originally analyzed 1000 videos from each category, but finding that YouTube had a considerably lower rate of relevant videos, we selected an additional set of 2000 YouTube videos from our gathered data set to analyze. One limitation of our approach is that recently tweeted videos are more likely to include popular videos than recently posted videos on YouTube; however no equivalent of "most recently posted videos" exists on Vine. For this reason, we conducted and report the analysis of YouTube videos and Vine videos separately. Once this initial set was gathered, we proceeded to filter videos that were authored by children and teenagers.

Filtering Youth-Authored Video

Amazon's Mechanical Turk (MTurk) is a flexible crowdsourcing service that enables various types of human computation, or the use of a human workforce to complete tasks that people can tackle better than computers [31]. Individuals and organizations called Requestors post short (as short as 10 seconds) HITs (human intelligence tasks). Individuals who respond to these tasks are Turkers, and are compensated in small amounts of money (as low as $0.01 per HIT). In addition to labeling images, typical tasks include sentiment analysis of text, writing product reviews, and transcribing audio [25]. Our goal for employing MTurk was to filter a manageable set of youth-authored content for in-depth content analysis from the large sample of YouTube and Vine videos that we had collected through our first-level filtering.

The default MTurk Requester UI offers a set of basic templates for creating HITs, such as a categorization template [2]. Based on our review of the initial set of 50 videos, we knew that we needed to include a confidence value or qualifier about the age of video authors. For example, some teens looked older than the ages they posted on their public profiles, and determining age without explicit profile data like this is a subjective process. MTurk's default categorization template did not afford us such qualifiers, so we implemented a modified HIT using the MTurk Command Line Interface (CLI) [3].

	YouTube	Vine
T1 & T2 both assign 4	120 (4.0%)	114 (11.3%)
T1 & T2 both assign 3 or 4	24 (0.8%)	89 (8.9%)
T1 & T2 rate other	2838 (94.6%)	797 (79.7%)

Table 1. Summary of Turker ratings (T1 = Turker1 rating; T2 = Turker 2 rating), focusing on those identified as youth-authored, some collaboration of youth and adult, and non-youth-authored.

We defined our HIT so that Turkers could identify five different categories of authorship, along with a rating qualifier that they could select if they felt their age judgment was "borderline" (i.e., the video creator might be 20 years old, instead of a teenager). We defined our video authorship rating categories as follows:

- *Rating category 0*: There is ZERO evidence about the video creator's age in the video (no voice, no face, etc.) or video description.
- *Rating category 1*: This video does not appear to involve a minor. That is, only adults are shown, or it appears to be a professional/company-created video.
- *Rating category 2*: This video appears to involve a minor, but not as its primary creator – e.g., a parent filming a toddler playing in the park.
- *Rating category 3*: This video appears to involve some collaboration between adult and children/teenagers – e.g., a parent may be recording or may host the video, but the child is directing the action.
- *Rating category 4*: This video appears to be authored by a child or teenager.

We introduced the rating system as follows:

> *Review and rate the video in the link provided based on whether you can tell if a minor (youth under 18 years old) created the video, or was involved in its creation in some way. …. If you cannot tell, or see no evidence anywhere that the video was created by a minor, select the "Zero Evidence" option.*

To mitigate any concerns of Turkers about our reasons for seeking out videos of and/or created by minors, we included a description of our IRB-approved research at the bottom of the HIT instructions: "*This work is part of an approved, academic research study on digital media created by youth. University researchers are conducting a study that focuses on the types of videos that youth (younger than 18 years old) create and share online*."

Beyond the typical MTurk requester issue of defining a HIT clearly so that it is easily understood and quickly taken up by Turkers, requesters typically face two challenges in developing effective HITs [31]:

- Ensuring quality control and accuracy of HIT results without incurring any excessive overhead for double-checking work; and
- Providing sufficient incentive/motivation for reputable

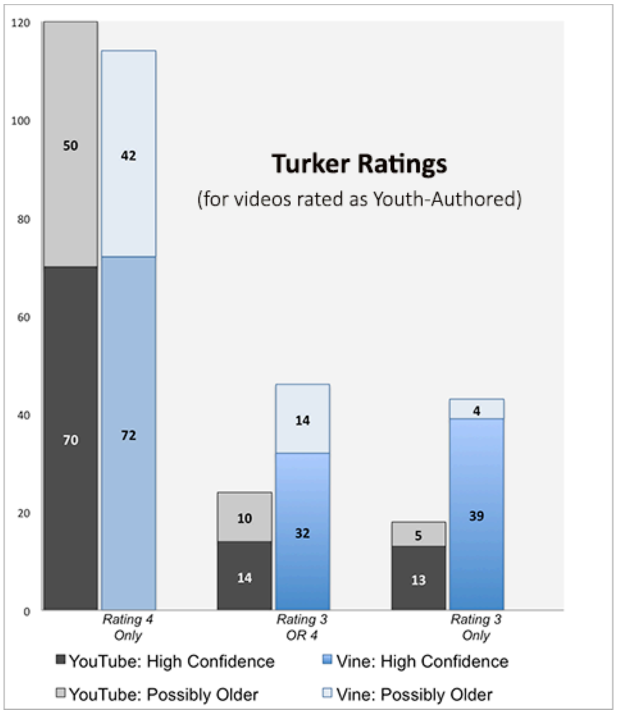


Figure 1. Breakdown of videos that Turkers identified as solely youth-authored (rating 4), either youth-authored or possibly a youth/adult collaboration (rating 3 or 4) or likely a collaboration (rating 3). The bars reflect those that were identified as "borderline" – i.e., author might be older than 18-years old.

Turkers to apply to complete their HITs.

To address quality control (QC), we included two QC measures [31] into our MTurk filtering process:

- *Reputation*: Only Turkers who met our qualification requirements were eligible; and,
- *Redundancy*: Two Turkers were assigned to each HIT, as a redundancy for selecting our subset of videos for in-depth content analysis.

In order to recruit high-quality Turkers who understood our video authorship identification task and could be reasonably expected to make "good" ratings about authorship, we developed a video-rating qualification test. Qualification tests are a "gold standard," or ground truth that reputable Turkers can earn to become eligible to complete more HITs and gain increased reputation in the MTurk crowdsourcing community. For requestors to implement qualification tests, they must use the MT Command Tool API (the default MT Requester UI templates do not include options for including a gold standard qualification test) [2]. To be eligible to accept our video-authorship HITs, Turkers first had to be identified as reputable in the MTurk community, based on earning a 95+% approval rate for HITs they had completed; and also complete our video-rating qualification test with a minimum score of 88%. We wanted to balance the number of qualifications required for our HITs and the number of Turkers who were eligible, while maintaining a fairly high level of quality in our results. We determined that two-Turker redundancy, coupled with high approval ratings and our own by-hand checks of the videos rated 3s and 4s, would still yield reliable results, so we opted to allow Turkers who may have had less experience, but consistently high approval ratings. As the study progressed, we found that very few videos were miscoded (only 5% and always with the "uncertain" of age qualifier added). This low error rate increases our confidence in the validity of the Turker responses.

To address the incentive challenge, we estimated the time to complete an individual rating based on our experience identifying authorship in our initial set of 50 videos, surveyed compensation averages offered for comparable HITs in the MTurk community, and reviewed Amazon's Requestor "Best Practices." We estimated that a HIT would take approximately 60 seconds to complete; however, to give Turkers ample time to review videos, we set a maximum time of 5 minutes per hit. We also settled on an average of $0.18 payment per approved HIT (MTurk requestors can choose to disapprove payment if a Turker consistently produces low quality work). Qualified Turkers rated the 4000 videos within 48 hours of launching our assignment (at 2 Turkers per video, we coordinated 8000 HITs). Turkers took an average of 55 seconds to complete each HIT, confirming our estimate. We conducted random QC of completed HITs, checking approximately 120 video ratings (3%), and approved all completed HITs. Based on the completion rate and overall quality of our results, we found that our MTurk-based filtering process is an effective alternative method for identifying and filtering youth-authored content on public video platforms.

Turker Results and Follow-Up Process

Results of our MTurk filtering process are shown in Table 1 and Figure 1. Table 1 provides the number of videos identified as youth-authored for each video-sharing platform. Overall, Turkers identified youth-authored videos in about 9.1% of our total sample of videos (365 of 4000 in raw numbers). Beyond the ratings shown in Table 1, we found that the age-qualifier that we included in our HIT was useful at highlighting videos that might need to be reviewed more closely or dropped from our in-depth analysis count. Figure 1 displays our Turker rating results as a breakdown of most likely youth-authored (both Turkers assigned the video a category 4 rating); youth-authored or youth/adult collaboration (one Turker identified the video as category 4, while the other identified it as category 3, or a collaboration between youth/adult); or most likely a collaboration (both Turkers assigned a category 3 rating). The figure also highlights the number of videos within each category that Turkers qualified their rating as one where "author is possibly older, or borderline age than 18 years old." Stacked within each bar, the lighter shade reflects those videos for which Turkers felt the author might be a young adult (19-21 years old) versus a minor (younger than 18). Turkers qualified their ratings 30-40% of the time.

Ethical Considerations

While this process examined only publicly shared videos, we carefully considered the ethical implication of studying and sharing these videos outside of their originally intended context. We carefully considered the balance of presenting our original data to support reinterpretation and reanalysis by the scientific community with the potential harms such presentation could bring to video authors. In order to protect the authors we take four steps. First, we only share videos that have already gathered a large audience (e.g., over 10,000 views), as we are unlikely to be introducing new unanticipated risks to those authors. Second, instead of archiving these examples, we include direct links to the public videos. This means that these links will only remain valid for as long as the authors choose to keep their videos public. We respect the creators' right to remove videos at any time. Third, all video creators were contacted to inform them we were linking the video and to give them an opportunity to opt out (none chose this option). Finally, all video screen captures are traced to remove identifiable features.

Content Analysis Process

The content analysis included two components: gathering posted data for each video and author (e.g., video views, video description) and data-driven content analysis where each video was viewed and analyzed by at least one researcher. To gather posted data from the YouTube videos and about the YouTube users, we used the YouTube API. Since no similar Vine API is available, we used Selenium and BeautifulSoup to scrape the posted information directly from the Vine video and user pages. The analysis of this data is presented in the following section.

Figure 2. Using our description schema, this video is described as "Two teenage boys act in a parody skit of a Popeye's commercial on a suburban street."
https://vine.co/v/MDAnu39pP2W

However, most of the information that was of interest to our research questions was not posted directly to the video and had to be hand-coded. In order to arrive at a consistent set of coding practices, we randomly selected and independently coded 20 videos from the filtered data set of youth-authored video. This four-rater agreement process was done on a randomly selected subset of videos rather than the entire video set to calibrate our practices and is considered an appropriate way of establishing inter-rater reliability and consistency [18]. This independent coding process included quantitative characteristics (e.g., estimated age of author), binary ones (e.g., is the child's face visible), and qualitative ones (e.g., open coded description of the video content). On the 20 videos, the four independent coders had strong agreement (Krippendorff's alpha = 0.83) on quantitative characteristics such as the estimated age of the minors involved. We had perfect agreement (Krippendorff's alpha nominal = 1) on binary characteristics such as whether the youth's face is visible or voice audible in the video. To compare our qualitative descriptions of the videos, one researcher pulled out 2–4 main keywords from each coder's open coded description. There was significant agreement between the coders as to the contents of each video, with 80% of keywords (or synonyms) appearing in all four raters' descriptions. We discussed disagreements and decided how to best focus our qualitative description of other videos. We developed a description schema for the remaining open coding to ensure that we included all pertinent characteristics of the video: "[Person(s)] [action] [of/about object] [if visible: location]" (see Figure 2 for an example). These descriptions served as textual data that we could cluster, use for axial analysis, and leverage to refer to specific videos as we considered new

	Vine Videos	
	Youth (n=205)	Non-Youth (n=749)
% Deleted 3 Mo. Later	10.7%	7.4%
Mdn. # Loops	1,433,000	985,000
Mdn. # Likes	23,300	12,500
Mdn. # Comments	1,370	758
	Vine Users	
	Youth (n=126)	Non-Youth (n=544)
Mdn. # Loops	14,600,000	12,100,000
Mdn. # Followers	25,600	17,800
Mdn. # Following	121	99

Table 2. Scraped characteristics comparing Vine videos marked by Turkers as youth-authored versus other videos on median characteristics of viewership (median was chosen because of the significant skew in this sample, reported in previous investigations of online video sharing).

	YouTube Videos	
	Youth (n=131)	Non-Youth (n=2743)
Mdn. # Views	88	1,700
Mdn. # Likes	3	27
Mdn. # Dislikes	0	4
Mdn. # Comments	2	73
%Deleted 3 Mo. Later	13.9% (from original n=37)	9.7% (from original n=846)
	YouTube Users	
	Youth (n=127)	Non-Youth (n=1472)
Mdn. # Videos	27	122
Mdn. # Views	3531	100,000
Mdn. # Subscribers	20	225

Table 3. Scraped characteristics comparing YouTube videos marked by Turkers as youth-authored versus other videos on median characteristics of viewership (median was chosen because of the significant skew in this sample, reported in previous investigations of online video sharing). Percent of videos deleted 3 months after MTurk ratings is only of the first batch of videos evaluated.

categories of video content.

After this coding calibration and discussion process, the remaining set of youth-authored videos was divided among the four researchers and open coded. Additionally, throughout this coding process, researchers culled the data set of any videos that did not fit our criteria, for example ones that were posted in curated collections rather than by individual contributors, and ones that were not original (e.g., captures TV show, batched upload with duplicate videos). This constituted 6% of the videos and they were removed prior to additional coding. Additionally, we reevaluated some cases where the Turker were unsure of their estimates of author ages; if two researchers agreed that the video author was older than 20, it was excluded from the data set (this constituted 5% of the videos rated as 3 or 4 by both Turkers). The culled data set consisted of 131 YouTube youth-authored videos and 148 Vine youth-authored videos (279 total).

Once we culled and open-coded the video list, we conducted another round of coding to cluster videos into categories of content. Since significant prior work already exists on video authorship practices (e.g., [30]), we opted for a directed rather than conventional qualitative content analysis of video content. While conventional content analysis is entirely inductive, a directed content analysis combines a deductive approach of coding for categories observed in the previous literature with an inductive approach for identifying new categories if any appear in the data (for more detail on directed content analysis, see Hsieh & Shannon [20]). Thus, we deductively assigned seven of the author-generated content categories (top 7 in Figure 4) identified by the Pew Internet Report on Online Video [30]. But, as we expected this list to be incomplete for youth authored video, we also conducted data-driven analysis of the open-coded description schema to identify additional and missing categories. The inductive analysis was conducted through a process of open coding descriptions of videos, memoing, and axial coding until relevant categories emerged from the data. As we arrived at our final set of categories (Figure 4), we conducted closed coding of the data set. Again, we randomly selected a subset of videos (30 videos) that were coded by two coders to establish inter-rater reliability in assigning these categories to the video set (as a suggested practice in [18]). As our agreement in the assignments of these categories was high (Krippendorff's alpha nominal = 0.87), we proceeded to independently categorize each of the remaining 249 videos.

API and Scraped Statistics

We gathered quantitative statistics to compare videos identified as youth-authored by the Turkers versus videos that the Turkers did not mark as youth-authored. We used the YouTube API and scraped Vine data to gather information about each video and the users who posted each video (some users posted multiple videos during the data collection phase). For these statistics, we excluded only videos that were deleted by the author before the Turker's estimation of the age of the author. Table 2 summarizes the characteristics of the Vine videos, which shows that generally youth-authored videos and youth users received as much or more attention than non-youth-authored videos. Table 3 summarizes the characteristics of the YouTube videos, showing that youth-authored videos on YouTube generally received less attention than other videos. Additionally, youth users on YouTube were less active than non-youth users in terms of median videos posted, views of those videos, and subscribers. An interesting characteristic of both data sets was that the authors removed a significant proportion of videos within the first three months of posting. Youth authors seemed to be slightly more likely than adult authors to remove posted videos. However, most interesting characteristics of videos could not be automatically scraped or gathered from the website, so we culled the set to most relevant videos (see "Content Analysis Process" section) and hand-coded the remaining videos.

	YouTube (N=131)	Vine (N=148)
Avg. Estimated Age	14.3	17.0
Avg. # Youths in Video	2.10	1.67
% Adult Collaborations	34.5%	17.9%
% Shows Youth's Face	76.2%	92.6%
% Youth's Voice Heard	88.5%	79.7%
% Inappropriate	1.54%	18.9%

Table 4. Age, collaboration, and rule-following characteristics of youth-authored videos on YouTube and Vine, including the estimated age of the author, number of youths appearing in the video, percent of videos that seem to have been created in collaboration with adults, percent of videos where the youth's face is visible and voice is audible, and percentage of videos containing inappropriate content (coded as significant violence, cursing, or sexual content).

Directed Content Analysis of Youth-Authored Videos

We coded the filtered and culled youth-authored videos for several aspects of their production characteristics (e.g., collaboration, number of actors on screen, etc.) and content.

Collaboration and Rule-Following Characteristics of the Youth-Authored Videos

In our situating study, many parents mentioned specific rules for their children regarding the videos they create. While we did not survey the parents of the children whose videos we coded, the survey did give us some insight into *potential* rules that *some* parents introduce for their children's online video. We coded the videos for some of the rules mentioned by those parents to see if any proportion of the youth-authored video followed these. Some parents mentioned that children were allowed to create remixed content or make videos about activities (e.g., video games, playing with toys) but not have themselves appear in the video. However, we found that youth faces appeared in 76.2% of youth-authored YouTube videos and 92.6% of youth-authored Vine videos. For videos where the author's face did not appear, we examined other videos posted on the same account. We saw only three examples of an account that seemed to explicitly follow the "no showing faces" rule: a YouTube account where the child only acted out videos with toys and two YouTube game streaming channel where no webcam was used. In all other accounts, the authors did reveal their faces in other posted videos, thus the omission of the face in the coded video seemed to be more a factor of production choice than following a consistent set of rules. Parents also mentioned having many guidelines about appropriate dress, language, and content in the videos, a topic we approach later in this section.

We coded for a number of age and collaboration characteristics of the posted videos (see Table 4). We wanted to know the average age of the video author in these videos, estimating it from evidence such as the video itself, the account description, and other videos on the account. We found that both children and teenagers of various ages shared YouTube videos, while Vine was mostly dominated by older teens. On both sites, our observations included children as young as 3 creating videos with an adult's help, up to teenagers judged to be between 19 and 20 (youths older than 20 were excluded from the study). Many videos were inherently collaborative, with multiple young people appearing in the same video. On YouTube, videos contained 2.10 children or teenagers on average. Many videos also contained adults, with most of these adults acting as active participants in the video creation (e.g., speaking on or off-camera, participating in the story, hosting the video on their account, etc.). We coded the videos that we viewed as active collaborations between adult and youths and found that a little over a third of YouTube videos fell into this category. On Vine, the average number of youth in the videos is 1.67 which is surprisingly high given the 6-second video length description. In many of these videos, other youths featured were younger relatives instead of peers. In contrast to YouTube, adults were rarely present in these videos. Collaborations with adults were also considerably less common than on YouTube, representing only 17.9% of the videos. All of these factors draw a contrast between YouTube as a family space for younger authors versus Vine as a playground for older teens.

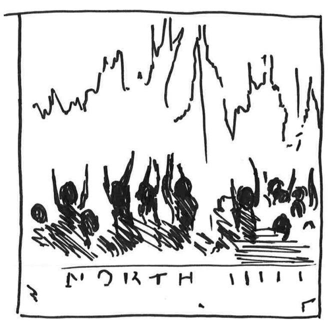
Indeed, the lack of following rules on Vine was also clearly represented with the significant amount of content that we coded as violent, sexual, or obscene. We were fairly moderate in tagging videos with this code, only including videos that two coders agreed were significantly offensive. In the violence category, this included several examples of vicious schoolyard fights, but not any of the more playful tussles or threats of violence. In the sexual category, we included several examples of frontal and back nudity, sex toys, and explicit sexual acts described in the video, but excluded simply using sexual words in non-sexual contexts or dancing in a manner that may be construed as sexual (e.g., "twerking"). In the obscene category, we included only videos that had more than one example of curse words, racial slurs, and obscene behaviors. We saw only two YouTube videos that had inappropriate content that fell in the "violent, sexual, or obscene" category (one depicted a schoolyard fight between two teenage women, the other video game violence and

Staged: Girls perform a choreographed dance.
https://vine.co/v/M9XPgVzX61u

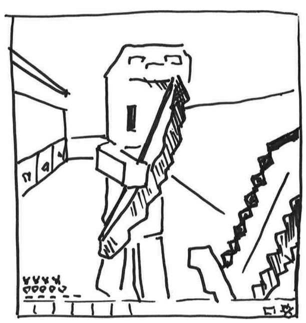
Everyday Things: Boy plays popular soccer video game.
http://www.youtube.com/watch?v=-EsBPUKWmTQ

Creative Remix: Combination of music video and popular vine
https://vine.co/v/MEn2TEpD0p5

Selfies & Opinions: Girl complains about her mom.
https://vine.co/v/hTQEVKqXjHJ



Event Attended: Student section participations in football tradition.
https://vine.co/v/MAgW9a6KuTe



Tutorial: Girl shows customization of popular game, Minecraft.
https://www.youtube.com/watch?v=eOdahoAsgEA

Acted Response: Recorded reaction framing another's Vine.
https://vine.co/v/MxJrZF23nOn

Funny Things: Demonstration of newly created dance moves.
https://vine.co/v/MvqDUz5z9On

Figure 3. Traced screenshots of examples of videos for each video category observed in the youth-authored video data set.

cursing). However, roughly 18.9% of videos on Vine videos posted by children and teenagers fell into this category. Additionally, we saw many examples of videos that would be considered homophobic (friends mocking each other about "knowing what ass tastes like"), misogynistic (young man expressing his opinion on women as "these bitches"), and racially charged (racial slurs, imitating what other races are "like").

Content of the Youth-Authored Videos

We used the directed content analysis method to categorize the content (see Figure 4) of the youth-authored video into each of the seven categories identified by the Pew Online Video survey [30], however we also identified two categories of video that were distinct. We describe each category and provide examples (see Figure 3):

1. **Staged, Scripted or Choreographed Activity** was a particularly common activity in youth-authored video with 62% of Vine and 28% of YouTube videos falling in this category. A common type of this on both YouTube and Vine was a performance, particularly singing, rapping, or dancing for the camera. However, Vine videos were also particularly likely to contain short skits (usually humorous) on a variety of topics. Many Vine accounts featured recurring skit topics and characters (e.g., a stern mustachioed father as acted by his teenage son).
2. **Videos of Doing Everyday Things** was a common category of video, found in 26% of Vine and 44% of YouTube videos. While the original Pew survey only included "videos of family and friends doing everyday things," we expanded this definition to include videos of self, as we observed that these included largely the same content as other "doing everyday things videos." This expansion is consistent with how other Pew categories were defined (i.e., "themselves or others"); however, it is distinctly different from the "video selfie" category in that it includes everyday activity rather than simply expressing an opinion at the camera. Examples of this included playing video games and spending time with friends after school. In one poignant example, a teen records himself in the everyday activity of going to a convenience store, capturing and commenting on the clerk of the store "unobtrusively" following him to make sure he doesn't steal anything.
3. **Videos of Themselves or Others Doing Funny Things** was a very common category on Vine (41% of the videos) but less common in the youth-authored videos on YouTube (15%). Humor seems to be a huge component of Vine videos and the youth frequently shared, acted (see #1 above), or re-enacted (see #9 below). The humor presented was typically in the form of action (e.g., funny dance move, falling), joke (e.g., "Is your refrigerator running?"), antics of younger children (e.g., mishearing song lyrics), or funny skit (e.g., imitating an awkward teacher).
4. **Creative Remix of Content or Material** includes creatively combining multiple sources of existing content (this is different from simply copying existing content to an account without modifying it). We observed this activity in 11% of Vine and 4% of observed YouTube videos. A common type of activity included remixing a video meme (e.g., a video of a girl in a car saying "broom broom" on Vine) with other memes or artistic content (e.g., music video).
5. **Videos of an Event They Attended** includes videos of sporting events, concerts, and other organized activities. These formed 6% of Vine videos and 9% of YouTube videos in our data set, examples including school sports events, large concerts, conventions, and parties.
6. **Video Tutorials or How To Videos** aim to educate the audience about a specific topic or teach a specific skill. 14% of the Youth YouTube videos fell into this category; the examples included a make-up tutorial from a teenage girl and a tutorial of a particular Minecraft skill from a young boy. There were no videos of this category on Vine, most likely because the 6-second format does not lend itself to tutorial-based sharing.
7. **Videos of Pets or Animals** were largely excluded from our data set (with only one example Vine video in this category). This is likely not a characteristic of authorship but rather that many pet or animal videos may not make it possible to distinguish the age of the author if they do not speak or reveal themselves in the shot. We did see examples of pet/animal videos outside of the data set but on the accounts of identified youth authors.

The two categories below did not appear in the previous work on online video, but represented significant or unique aspects of observed youth video authorship:

8. **Video Selfies & Expressing an Opinion** is a common category of youth-authored video with 25% of YouTube and 15% of Vine videos falling in the category. In videos of this category, the youth looks directly at the camera and either expresses an affected action (e.g., smooching the camera, making faces) or a specific opinion (saying, "If you tell me to text you, you need to text back, stupid;" expressing a negative opinion of a specific video game, etc.). These videos generally seemed fairly staged and had a performative, spoken-word quality to them.
9. **Acted Response** is a new category of video that we identified on both Vine (5%) and YouTube (4%). Unlike the "creative remix" category, acted responses included new content, featuring the author of the video. Two categories of acted response were "framing" and "re-enacting." Framing involved including clips of others' content in an acted story. For example, one teenager edited another's video of children getting in trouble into a skit about the perils of babysitting. In many other examples, teenagers would include a clip of another's video framed by their own response to that video. The

second category of acted response was re-enacting a popular video. For example, one viral video showed a teenager hearing a favorite song, beginning to dance to it, and then slipping and falling. Several other Vines reenacted this video, with the same music, dance, and resulting fall but in different contexts (e.g., wet floors, tripping on a dishwasher door, stepping on a running treadmill). On YouTube, this category consisted of youths reenacting music videos, movie scenes, or other popular videos.

We must emphasize that many of the videos fell into multiple categories, for example in one video a teenager recorded a funny (category 3) skit (category 1) framing as an acted response (category 9) to a popular Vine meme.

Limitations and Cautions

There were several limitations to our approach. The first two limitations focus on identifying youth authors from videos and user accounts, which was an ambiguous process. First, many videos and accounts do not give any clues as to the age or identity of the authors. Those videos received a rating of 0 from the Turkers and were not included in the analysis, but could have potentially been authored by children or teenagers. One symptom of this problem may be the dearth of videos about pets/animals in our sample, since those would not have been identified if the author does not speak or appear in the video or provide any clues about their age elsewhere on the account. Second, although each video was rated by two qualified Turkers, many Turkers disagreed on their ratings. We decided to exclude those videos with rater conflict of more than one point from our coded collection, and only consider videos with ratings of 3 or 4 from both Turkers. In practice, this also means that we may have missed some relevant videos from the set. Overall, we can vouch for the high precision of our final data set, but not for its recall.

There were also two limitations to our coding. Several findings may be affected by our estimations of authors' age. There were several borderline age examples in the Turker filtered data set. We removed such videos from the analysis when two researchers agreed the author was likely over the age of 20 (5% of the videos). However, the estimated ages of our video authors came from the best guesses of the researchers based on the available data. Although we cannot guarantee complete accuracy, we did have high inter-rater agreement in these estimates and therefore fair confidence they were reasonable. Finally, 6% videos in our sample came from user accounts that may not represent a single author. These included curated accounts on specific topics (e.g., funny kid videos) and collection accounts where no individual contributor was identified (e.g., account collecting videos of sport games of a specific high school). We resolved this by removing these videos from analysis, but better handling of collection accounts may add new insights in the future.

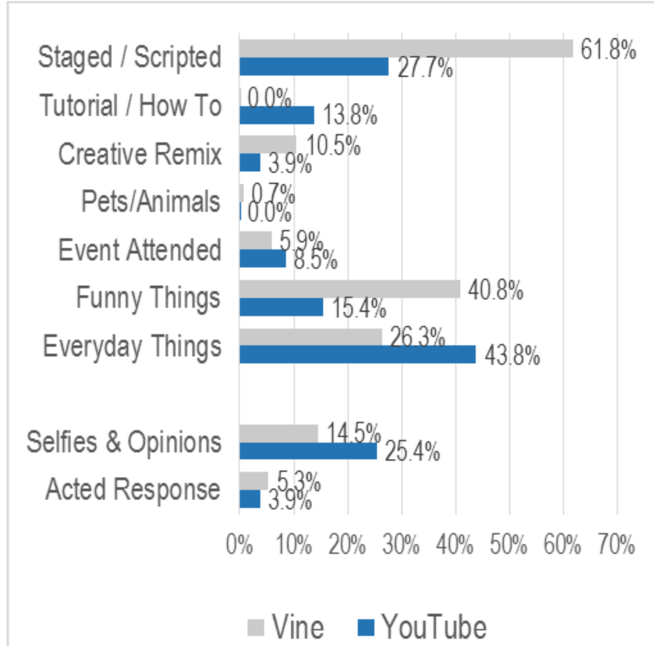


Figure 4. Percentage of Vine and YouTube videos in each content category identified in the Pew Online Video survey [30], as well as two new categories identified in this work (Selfies & Opinions and Acted Response).

DISCUSSION

In our study, we saw examples of children and teenagers as active video content creators. Even with conservative filtering (i.e., discarding videos without age evidence, discarding videos where raters disagreed on age), youth-authored videos composed 3% of the YouTube videos and 17% of the Vine videos. In this section, we reflect on our content filtering approach, discuss our findings in light of previous work, and end by considering some implications and opportunities for design.

Reflecting on Crowdsourced Content Filtering

The filtering approach we took in this work worked well at identifying a relevant data set for analysis. While this kind of filtering may seem obvious in retrospect to crowdsourcing experts, it has not been used in previous studies and presents an interesting alternative to the growing approach of search-based selection for video-based content analysis [5,19]. In the process of developing the method, we found that it was more complex than a standard "categorization" task and we describe the specifics of our approach to addressing this complexity in the section "Filtering Youth-Authored Video." Others may be able to use a similar approach to video analysis, as it can also be adapted to support other situations where a human can easily categorize a video but a computer may struggle. For example, in our dataset of videos, we saw many racially charged discussions. Turkers could help filter videos by African-American Viners to help understand the unique perspectives and stories of this group on Vine. Additionally, crowd-filtering methods can be combined with traditional keyword search approaches. For example, somebody studying video game experiences could first search for video gamecasts of relevant games (e.g., “WoW,” “LoL”) and then ask crowdworkers to filter based on the specific game behavior of interest (e.g., video creator losing the game). However, we acknowledge that there are significant opportunities for improving this method by considering alternative approaches to redundancy and validation. There may also be an opportunity for crowdsourcing to enable larger scale video analysis by incorporating “crowd” stages at key points in the process. For example, while developing categories of content required a “bird’s eye” view of the qualitative data to ensure capturing important patterns in the data, the final process of labeling videos with appropriate categories can easily be adapted as a crowdsourcing request to allow for larger scale analysis.

YouTube is a Family Space, While Vine is a Playground for Teenagers

Through this work, we saw many differences between the youth-authored content on Vine versus YouTube. Some of these differences were undoubtedly due to the specifics of the medium. For example, the 6-second format of Vine does not lend itself well to video tutorials or how-to videos. However, other differences may be due to the community and practices of each website. We found that the YouTube creators were on average younger, more likely to collaborate with adults on the videos, and much less likely to include inappropriate content. In our situating study, parents expressed that they were aware of YouTube and monitored their children’s activity on the site. On the other hand, Vine authors were mostly mid- to older-teenagers, who were not as likely to include adults as collaborators in the videos, and were much more likely to post inappropriate, vulgar, or risky content. The age difference between the platforms may be explained by the younger “recommended” age of YouTube creators (13+) versus Vine creators (17+) (though, we saw creators younger than these recommended ages on both sites). While both sites moderate content and have policies for limiting access to adult content (e.g., clicking to confirm age on certain videos), our study has revealed that the *de facto* moderation practices on Vine may be looser than those on YouTube.

Though it is easy to discount inappropriate content as a parenting failure, it is also important to remember that teenagers “fashion themselves” through their language in contexts like this [14], faceting and exploring their identities through risky content creation [12,27], and developing coping and resilience skills for later online interactions [37]. It is also important to acknowledge the creative behaviors that characterized Vine, such as building on each other’s work through remixes and acted responses that were reminiscent of playground play [13], including playful mimicry and storytelling. Clearly, YouTube and Vine video sharing sites each offer a distinct flavor of creative platform that highlights differing, yet equally important expression values.

Adults May Use Online Video as *Archive*; Youth Use Online Video as *Stage*

We cautiously compared adult and child video practices. Pew Internet Research conducted a large-scale questionnaire asking adults about the content of their shared online videos across platforms [30]. Since their study and ours did not use the same methodology (self-report versus content analysis), we do not make direct comparisons between percentages, but we do examine the relative popularity of each category. The Pew study found that most users reported sharing the following top four types of videos (in order from most to least reported):

1. Videos of friends and family doing everyday things
2. Videos of themselves or others doing funny things
3. Videos of an event they attended
4. Videos of pets or animals

In contrast to this, the top four most common types of videos found in our youth-authored data set (combining data from both Vine and YouTube), included:

1. Intentionally staged, scripted, or choreographed videos
2. Videos of friends and family doing everyday things
3. Videos of themselves or others doing funny things
4. Video selfies and expressing opinions

Comparing the Pew data set of adult video authorship [30] with our own investigation of youth authorship, it could be hypothesized that adults view online video as an **archive** to collect and keep precious memories of everyday life with their family, friends, and pets, humorous moments, and special events. In contrast, children and teenagers treat online video as a **stage**. In our data set, we saw them using online platforms mainly to perform (dancing, singing, skits), tell stories (whether capturing their everyday life or staged), and express their opinions and identities in a performative way (see Figure 3). These are preliminary hypotheses that stem from examining both studies; future work may find it fruitful to include a more direct comparison of *intentions* in both adults and youth video posts.

Staging and sharing of the performative youth self in online contexts highlights the way that interactions with media forms shape youth identities in the 21st century, corroborating identity development processes of staging and performativity first written about by sociologist Erving Goffman [15,16]. Thought of in this way, youth use Vine and YouTube videos to present social performances starring themselves, directed at a digital global stage, in ways that often subvert traditional notions of dramaturgical performance. Backstage and front stage divisions are blurred: home spaces become public areas; hidden habits like grooming are broadcast; taboo props like toilets are made acceptable and included as part of the stage; and the messiness of video making is reflected openly in finished commodities. The techniques, tropes, and language used by youth reflect a melting pot of media approaches, adapted and reshaped from genres of reality television, comedic parody news media and popular online celebrities. These remixes reflect the currently dominant viral flow processes of modern video media [28], embedded in an always connected world, in which media engagement is a tri-fold process that incorporates attention, affinity and extension or diffusion of existing content in new ways [1,29,36].

Implications and Directions for Technology Design

We set out with one goal being the consideration of children's online safety, but it may be important to explore counterpoints as well, acknowledging that the idea of online safety can be taken to an extreme. For example, Google recently released a new application called YouTube Kids, which limits content to popular children's programming and "kid-friendly content from filmmakers, teachers, and creators." The official app description boasts that it screens out "videos that make parents nervous" and only shows "videos that parents can feel good about" [45]. While YouTube Kids is targeted at a younger audience than those studied in this paper, it is representative of common attitudes towards online safety of minors. While it is certainly admirable to protect a vulnerable population, this seems to stand in stark contrast to the online youth creative communities we have observed in this study. Reducing children and teenagers to content consumers rather than empowering them as creators, we may be doing a disservice by quieting their voices and taking away their agency. Certainly, there was *plenty* in the videos we observed that would "make parents nervous," but this activity was authentic and meaningful in its own way. We saw youth-authored videos that explored complicated ideas like race, gender, sexuality, and violence in ways that were both vulgar/offensive, but also (and sometimes simultaneously) in ways that were reflective and personal. Examples included: teenagers passionately arguing about race on camera, a video selfie of a young women "telling off" men who objectify her, a video of a teenager discussing her sexual orientation and "telling off" "haters" in a rap performance, and a black teenager capturing on-camera discrimination against him. As others have pointed out [7,32], sometimes discomfort can be a productive place to be.

To consider next steps for design, we reflect on three points taken together: (1) parents worry about their children presenting themselves online in socially-acceptable ways (e.g., previous work [40] and our situating study); (2) youths use online spaces like Vine to experiment with their identity in sometimes violent, sexual, or obscene ways (one of the findings of this work); and (3) this type of identity experimentation has been shown to be particularly important to youths developing resilience in the long run (e.g., previous work [37]). Considering these three ideas in concert points to specific challenges for technology to support youth online video authorship practices. As an alternative to controlling what youth authors post online, we can consider technologies that empower the authors to reflect on their content and manage their self-presentation. As youths use the online playground of video sharing communities to explore their identity, we should design tools that can help this exploration be a less permanent part of their online presence. One such idea may be designing an NLP tool that crawls an author's videos identifying ones that may contain offensive language so that the author can have the option of removing those or making them private as they move into adult life. Considering that many of the authors in this study posted dozens or hundreds of videos, such a tool would considerably simplify managing self-presentation. Another idea may be supporting smarter video deletion. We saw that many children and teenagers delete their videos within the first three months of posting it (and many may wish to delete some of their videos in the future). Unfortunately, due to the high rate of user-copied content sharing online [11], deleting one's own video post may not prevent its continued distribution. A tool to help the author crawl content sites identifying content they own and would like to remove could help authors retain control of their content and their presentation of self. However, one challenge that arises in this scenario is dealing with remixed content or content that has been modified with a framing Acted Response. There are obvious questions as to who owns the new digital artifact that has been created through this process. Besides the two extremes of giving the original versus the editing author complete control of the content, as automatic video processing technologies improve, we may be able to offer better in-between alternatives such as automatically censoring identifying content in the original author's portion of the work or converting the original portion to a less identifiable format through a process like automatic cartooning.

CONCLUSION

In this work we examined the content that children and teenagers author and share on public video platforms (specifically, YouTube and Vine). In order to identify youth-authored videos, we proposed and piloted a new filtering method that leverages crowdworkers to filter relevant content for additional analysis. We coded filtered videos by hand to identify the type of content that each video shared. We found that youth videos have a content type not previously identified in studies of online video content sharing: "Selfies & Opinions." We also found an unusual style of creatively building on the work of others—a content type we titled "Acted Response." We identify important differences in youth video authorship on YouTube and Vine, particularly that Vine videos included significantly more violent, sexual, and obscene content. Finally, we build on previous work to tentatively contribute the contrast that adults may use online video as an *archive*, while children and teenagers use online video as a *stage*. Our findings reveal unique aspects of and opportunities for supporting youth video authorship.

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