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The NIOSH Agricultural Centers' YouTube Channel: Time Series Modeling of Viewership of Agricultural Health and Safety Videos

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ABSTRACT

We sought to understand the mechanism underlying the growth trajectory in the United States Agricultural Safety and Health Centers YouTube channel. We also explored the benefits and limitations of using YouTube analytics to evaluate the impacts of public health interventions involving YouTube. Time series analysis of total views, total watch hours, average duration of watch time, and number of subscribers were assessed to determine the monthly patterns of non-seasonal and seasonal components in the data from 2013 to 2020. Health, safety, and animal handling video views were summarized descriptively across time and season. Lastly, time series regressions were used to determine the type of video that best predicted growth in the channel viewership metrics. The time series were not random but could be explained by autoregressive and moving average correlation structures. Health videos were the strongest predictors of future growth but were not the most watched type of video. Strong seasonality components indicated that videos were most watched during periods of high agricultural activity, but less so during the winter months. Generally, growth in YouTube viewership metrics was explained by past month viewership predicting future viewership. Outreach and media content may produce spikes of increased interest, but in order to sustainably grow the channel over time, Ag Centers and other agricultural stakeholders should continue to focus on the value of particular content to potential viewers, how and when content is released, and strategic promotion of the channel and its videos.

KEYWORDS

YouTube; Social Media; Collaboration; Niosh; Agricultural Safety and Health; Training

Introduction

YouTube is a powerful online video sharing platform that has over 2 billion visitors who log in each month.[1] Over a billion hours of videos are watched every day on the platform, with over 70% of views coming from mobile devices.[1] YouTube connects with more people in a day than any television network in the United States (U.S.).[1] According to a recent study from the Pew Research Center, about 81% of U.S. adults use YouTube, and use is highest among young people.[2] Although use of the platform is slightly lower in rural areas of the U.S. (74% vs. 84% in urban areas), YouTube is still the most widely used social media platform in rural areas of the country, even though broadband access may be limited.[2]

Agricultural commodity groups have recognized that YouTube is a valuable platform to connect and engage with consumers.[3] However, aside from connecting with consumers, YouTube is also an important communication tool and information repository that is often used to access health education and workforce training resources.[4] Recent studies have documented that workers prefer visual health and safety information that is easily accessible such as through online videos posted on YouTube.[5,6] Using YouTube for health education and workforce training requires that content creators be viewed as credible. A recent study found that factors affecting perceived information credibility on YouTube included trustworthiness, quality of content, and

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engagement with information.[7] This report describes the growth of the collaborative YouTube channel of the U.S. Agricultural Safety and Health Centers.

Agricultural safety and health centers in the U.S

In 1990, the Centers for Disease Control and Prevention through the National Institute for Occupational Safety and Health (NIOSH), established the U.S. Agricultural Centers (Ag Centers) to conduct research, education, and prevention initiatives. The Centers work to address elevated rates of occupational injury and illness associated with the agriculture, forestry and fishing (AFF) sector. AFF workers experience some of the highest fatal and non-fatal injury rates of all occupational groups. In 2018, a fatality rate of 23.4 deaths per 100,000 full-time AFF workers was recorded, compared to 3.5 deaths per 100,000 full-time workers for all other U.S. industries combined.[8] Currently, there are 11 Ag Centers (10 NIOSH-funded AFF centers and the National Children's Center for Rural and Agricultural Health and Safety) geographically distributed throughout the U.S. to respond to the health and safety needs of people working in agriculture in their designated regions.

A primary mechanism of cross-center efforts for disseminating safety and health information is the maintenance and promotion of the Ag Centers' YouTube channel. The collaborative effort involves producing, reviewing, editing, uploading, and promoting videos; each of the Ag Centers contribute to this project. A previous report detailed the establishment of the YouTube channel in 2013, the process of video submission and review, and provided background about how the channel provides a platform for training and education that can be accessed in remote, rural regions where access to traditional, in-person training may be limited.[9] As of December 2020, 165 videos had been processed and uploaded to the site. Videos have been produced in English (n = 114), Spanish (n = 44), and K'iche (n = 7) to meet the needs of diverse agricultural workers and employers, including small farm operations and agribusiness, with the goal of providing quality health and safety information from a credible source. The analytics provided by YouTube including the number of subscribers, number of views per video or by category of video and watch time can be a valuable tool for assessing the reach of the educational content and engagement with viewers.

This study provides an in-depth investigation into the trends in the YouTube channel usage beginning October 2013 and extending through December 2020. Because the number of videos on the channel increased over time, time series analysis was used to explore three research questions: (1) What is the underlying mechanism of monthly growth in viewership since inception of the channel; (2) How does the type of video published vary across years and seasons; and (3) How has the type of video or number of videos influenced the growth of the YouTube channel. We hypothesized that viewership growth would be nonrandom but would likely be an autoregressive model, that the type and number of videos would influence this growth pattern, and that we would see seasonal differences by type of video. This study was motivated by a desire to understand the growth trajectory and provide other organizations using YouTube for information dissemination and public health interventions with an understanding of what questions can be asked and answered using YouTube analytics.

Methods

Procedures

YouTube analytics data were downloaded from the YouTube channel site for the period of October 2013 through the end of December 2020. We chose to assess total views (i.e. defined as watching 30 s of a video or more), total watch hours, average duration of watch time, and number of subscribers. A monthly time interval was chosen for the time series analysis because of the impact of health and safety awareness events where there were large spikes in YouTube channel views that caused a "shock" to the otherwise stable time series. Additionally, the limited number of videos published suggested that using a monthly interval was the best choice to assess video impact and keep the analyses on the same scale as the viewership channel data. A total of 87 months were used in the analyses.

The 165 videos were divided into three categories: health, safety, or livestock handling. Promotional videos were excluded because they are not designed to address health and safety issues in agricultural workers. The resulting categorization yielded 43 health, 56 livestock handling, and 53 safety videos for a total of 152 videos included in the time series analysis. To prepare the video file for time series regressions, we made three variables representing each of the categories and created a variable for each month that represented a sum of each video published up to that current month. We also created a running sum of total videos by month. The final analysis file contained a column for the month and year, three columns for each of the number of safety, livestock handling or safety videos summed up to that month and year, and a final column containing a running sum of the total number of videos posted each month.

Data analysis

The four channel variables (i.e., number of views, watch hours, average duration of views, and number of subscribers) were first converted to a time series and tested to assess whether they were serially correlated or whether they were random (white-noise) using the Ljung–Box Test.[10] The Ljung–Box test is designed to test for autocorrelation in the residuals of modeled data points; significance is based on the chi-square test. Next, we assessed whether each of the channel time series was stationary. Time series model building requires that the mean be constant across time points. We used the Dickey Fuller Test to find the differencing coefficient that would create a stationary time series and set the alpha at 0.05.[11] This test checks for a trend by regressing the differences in the residuals between two time series on the previous residual for each data point. The t-test is used to assess whether the null hypothesis holds and the series is stationary. We tested for differencing in seasonality of the time series using a test that minimizes the mean absolute scaled error.[12] Analyses were conducted in the R package forecast.[13]

To address question 1, we characterized the time series model that explained the changes in number of views, number of subscribers, watch hours, and average duration of views. The time series were graphed to determine whether the series showed consistent patterns, seasonality, stationarity, and homogeneity of variance. The autocorrelation function and partial autocorrelation function graphs were plotted to determine whether an autoregressive (AR), moving average (MA), or autoregressive-moving average (ARMA) model best fit the data, and with or without a seasonality component. The Akaike Information Criterion (AIC) was used to assess model fit for competing models. After determining the appropriate differencing coefficients, we assessed the order in the non-seasonal and seasonal components by testing AR, MA and ARMA models until a well-fitting model was identified. Residuals were plotted and tested to assure that they looked like white noise using the Ljung-Box Test,[10] were normally-distributed, and showed a constant variance.

An autoregressive model of order one, AR(1), means that regressing the current viewership metric on the previous month's viewership metric explains the serial correlation in the data. The order describes how many previous lag periods are needed to predict the current period. The moving average model of order one, MA(1), is similar to the AR(1), but rather than using the previous observation's value, it includes the previous forecasted error term to best predict the current value of the measure. The error term in the previous month is related to a "shock" or unusual peak of activity that occurred. The moving average measures how long it takes for the series to return to its expected level of activity after the "shock". An autoregressive-moving average, ARMA(1,1), model is best fit using both the previous value of a measure and the error term from the previous time point. The four viewership time series were plotted to show the monthly trends using a locally weighted scatterplot smoothing (LOESS) curve and separate plots were produced to show seasonality in each year of data.

To address question 2 and describe how trends by type of video varied across years and seasons, YouTube data were analyzed in Microsoft Excel (Redmond, WA). Pivot tables were used to summarize the number of videos published and views by category over time. Summary statistics available for viewer data in each video category included traffic source, device type, and subscriber status. An additional variable, "season" was coded into the dataset to determine which part of the year the videos were being viewed.

To assess the influence of number and type of video on the channel view characteristics described in question 3, we conducted time series regressions. We included the number of health, safety, and livestock handling videos for each month as covariates. In a separate model, we used a single covariate representing the total number of videos published at each time point in the time series. We report the slope coefficients, standard errors, t-tests, p-values and adjusted R^2 values for the models. The model coefficients are interpreted as in other linear regression models where a one-unit change in x produces an effect estimate for the dependent variable but allowing the dependent variable to be a time series.

Lastly, we forecasted 24 months into the future to project what the YouTube channel viewership would look like in December 2022. These results can be used to assess progress at achieving the goals of increasing channel engagement and use.

Results

Channel time series characteristics

Each of the four channel viewership time series were non-random, suggesting an underlying mechanism that describes channel growth (Figure 1). The differencing coefficient for the time series using one-month intervals was one lag for the total number of views, watch hours, and average duration of watch time per viewer. No differencing was needed for the number of subscribers. No evidence of non-stationarity was seen in the seasonal component of the any of the time series examined.

Channel time series growth mechanisms

All models were best fit using an order of one, where current observations were influenced by only a single previous lag (month) (Table 1). For the total number of views, the underlying mechanism that best explained the observed time series was the moving average for the non-seasonal component, MA(1), and was a negative relationship. The seasonal component of total views had both an AR and a MA, ARMA(1,1), component so that both the previous month's actual views and the error term together predicted the next month's views. The total watch time had only a seasonal component with AR(1) correlations. The average duration of watch time per viewer had an AR(1)

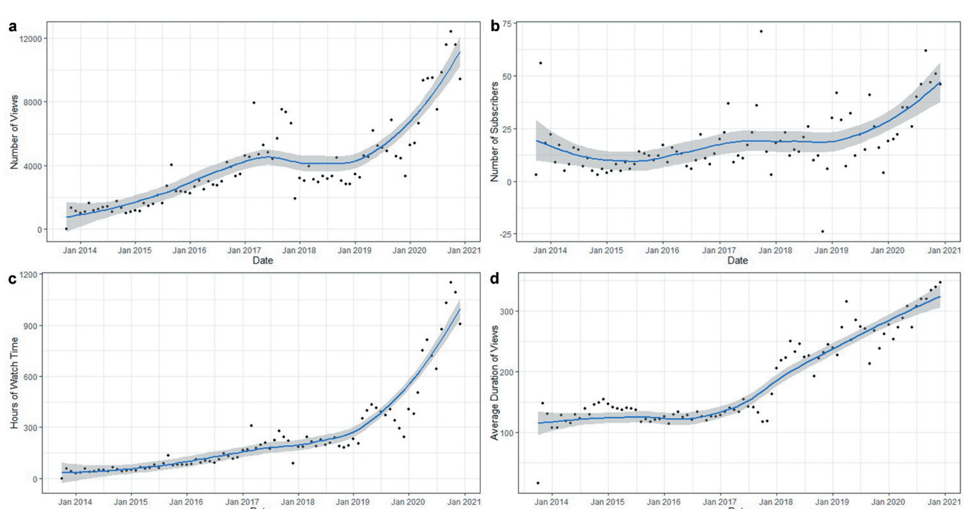

Figure 1. Time series graphs showing monthly total views, total watch hours, average duration of watch time and number of subscribers, October 2013 to December 2020.

Table 1. Time series models of four YouTube channel metrics to assess trends in viewership from October 2013 through December 2020.

Channel Feature	Non-seasonal component		Seasonal component	
	Autoregressive Estimate (SE)	Moving average Estimate (SE)	Autoregressive Estimate (SE)	Moving Average Estimate (SE)
Number of Views	–	−0.24 (0.12)	0.90 (0.12)	−0.69 (0.21)
Watch hours	–	–	0.49 (0.13)	–
Average duration	–	−0.39 (0.11)	0.24 (0.13)	–
Subscribers	0.26 (0.15)	−0.85 (0.09)	–	–

–Indicates that the YouTube metric lacked this component in it time series structure.

seasonal component and a moving average MA(1) non-seasonal component. The number of subscribers did not have a seasonal component, but the non-seasonal component followed an ARMA(1,1) model fit. The fact that all MA(1) components, seasonal and non-seasonal, were negative indicates that reductions in the random error in the previous time points predicted a future time point. Seasonality can be seen in three of the time series across all years (Figure 2).

Descriptive data on video trends across time

From October 2013 to December 2020, the 152 videos analyzed had a cumulative 341,929 views and a total watch time of 21,012 hours. The safety videos (n = 53) were the most viewed with 192,210 views (56%), followed by livestock handling videos (n = 56) with 96,544 views (28%), and health videos (n = 43) with 53,175 views (16%). Each category is represented in the channel's top 5 most viewed videos. *Following Proper Grain Bin Entry Procedures Saves Lives*, first published in October 2013, continues to be the most watched video with 81,515 views, which is 42% of all the views in the safety category. The Spanish language *EPA Pesticide Safety* video, published in January 2017, is the most frequently viewed video in the health category. It has been viewed 15,942 times and accounts for 30% of all health video views. The most viewed livestock handling video is *Outside Animal Care (Dairy Safety Training Part 1, Section 1)*. Since publication in December 2013, it has been viewed 10,352 times and accounts for 11% of the livestock video views. The second and third most viewed videos on the channel are parts 1 and 2 of *How to Use a Chainsaw Safely*, which since publication in December 2015, have been watched a combined 65,003 times. Table 2 shows the seasonality of each type of video.

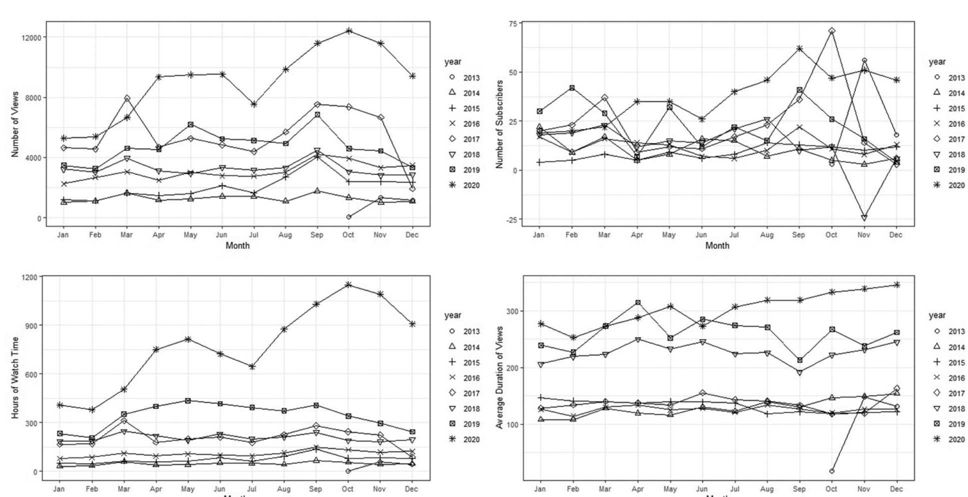

Figure 2. Seasonality plots showing monthly total views, total watch hours, average duration of watch time and number of subscribers, October 2013 to December 2020.

Table 2. YouTube views by season for three types of health and safety videos, 2013–2020.

Video Category	Spring n (%)	Summer n (%)	Fall n (%)	Winter n (%)	Total n
Health (n = 43)	17,496 (33)	14,210 (27)	10,759 (20)	10,710 (20)	53,175
Livestock Handling (n = 56)	23,611 (24)	23,794 (25)	27,432 (28)	21,707 (22)	96,544
Safety (n = 53)	42,959 (22)	46,263 (24)	69,120 (36)	33,868 (18)	192,210

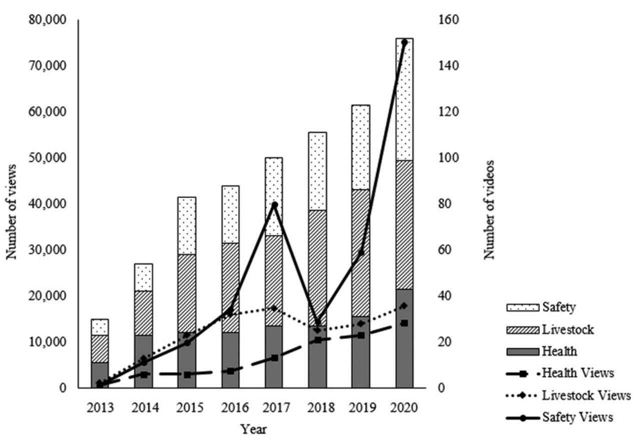

Figure 3. Clustered columns represent the number of videos available each year by category. the lines indicate the number of views each year by category.

Figure 3 illustrates the number of videos by category added to the channel each year, compared to the number of views in each category. By the end of 2015, there were 24 to 34 videos in each of the three categories. Between 5 and 12 videos were added each year from 2016 to 2018 before 29 videos were added in 2020. The majority of recently added videos were safety related, and views for safety videos increased 156% from 2019 to 2020. No new safety videos were added in 2018, which showed a dramatic decline in viewership.

Videos in each of the three categories were mainly viewed by non-subscribers (between 96 and 99% of views), but the videos for each category were accessed differently. The traffic source analytics indicated the majority of viewers accessed the health videos through external websites (26.4%), the livestock videos through YouTube searches (21.4%), and the safety videos through suggested videos (37.7%). Viewers accessed videos in all three categories mostly through computers than through mobile phones. For health videos, 69% of views were from computers and 23% were from mobile phones. Similar numbers were reported for livestock handling videos with 61% of views through computers and 28% through mobile phones. The safety videos were viewed through computers only 47% of the time, with an additional 40% of views with mobile phones.

Time series regressions

The health videos were significantly predictive of total views and total watch time ($p < 0.0001$); less so were the livestock handling videos ($p = 0.04$) (Table 3). The safety videos were not significantly predictive of any of the viewership metrics and showed a consistent negative association with viewership measures. The negative coefficient likely reflects the use of these videos for training purposes. Once they are completed, they are not driving future use or prompting users to seek additional information. This does not indicate that the safety videos are unimportant, it simply reflects whether they are promoting additional views in the following month.

Video type did not predict the number of subscribers and explained little of the variance in the model ($R^2 = 0.14$); however, video type explained greater than half of the variation in the time series models for total views ($R^2 = 0.61$), total watch time ($R^2 = 0.59$), and average duration of views ($R^2 = 0.64$). The adjusted R^2 values for the types of videos were similar to those for the total video counts (number of subscribers = 0.14, total views = 0.56, total watch hours = 0.52, average duration of view = 0.64). In social science fields, an R^2 of 0.64 is considered a strong effect; the recommended practical significant effect size is 0.41.[14] With the exception of number of subscribers, three viewership measures reached this recommended level for a meaningful effect.

Results from the forecast indicate that by December 2022, total views are projected to increase by 34.8% (9,418 to 12,699), total watch time to increase by 53.2% (907 to 1,390), average duration of watch time to increase by 6.4% (346 minutes to 368 minutes), but number of subscribers is projected to decrease by 10.9% (46 to 41).

Table 3. Effect estimates and standard errors (SE), t-test, and adjusted R^2 from channel viewership models with video type and video counts as covariates, 2013–2020.

Type of YouTube video	Estimate (SE)	t-test (p-value)	Adjusted R^2
Total Number of Views			
Health videos	302 (71.0)	4.26 (<0.0001)	
Livestock handling videos	86.1 (40.2)	2.14 (0.04)	0.61
Safety videos	-91.9 (61.3)	-1.50 (0.14)	
Video Count	70.9 (6.70)	10.6 (<0.0001)	0.56
Total Watch Hours			
Health videos	31.6 (6.78)	4.66 (<0.0001)	0.59
Livestock handling videos	7.92 (3.84)	2.06 (0.04)	
Safety videos	-11.2 (5.86)	-1.91 (0.06)	
Video Count	6.39 (0.65)	9.80 (<0.0001)	0.52
Average Duration of Views			
Health videos	4.22 (1.84)	2.30 (0.02)	
Livestock handling videos	2.65 (1.04)	2.55 (0.01)	0.64
Safety videos	-0.23 (1.59)	-0.14 (0.89)	
Video Count	2.02 (0.16)	12.3 (<0.0001)	0.64
Number of Subscribers			
Health videos	0.93 (0.58)	1.60 (0.11)	
Livestock handling videos	0.17 (0.33)	0.50 (0.62)	0.14
Safety videos	-0.19 (0.50)	-0.39 (0.70)	
Video Count	0.20 (0.05)	3.89 (0.0002)	0.14

Discussion

We found that channel viewership grew in a predictable manner and was not random. Health videos were a strong factor in explaining the observed growth, and there was a strong seasonal component. We predict that the growth in at least three of the four metrics assessed will continue. Our study documented the mechanism underlying the growth in viewership in the U.S. Ag Centers' YouTube channel. It also highlighted the types and number of videos and how viewership varied across years and seasons.

The mechanism that created each of the time series informs us as to what is driving future viewership. Assessing only the non-seasonal effect, total views, average duration of views, and number of subscribers showed a one-month change after a "shock". These "shocks" are most likely a result of Ag Center outreach events and activities that draw attention to specific agricultural safety and health videos and create a spike in viewership, except for watch time, which was unaffected by these one-time events. We theorize that the reason for the uptick in the past two years is because the channel is maturing. It receives a greater number of views from the YouTube "suggested video" feed because of the number of views. We have had additional social media campaigns by all Centers that have included links to videos. More videos are used for trainings, e.g., grain safety and feed yard trainings, and we have added more videos on the site in the past few years. Also, people are referring others to the site and there has been greater recognition of Center work with increased marketing. The negative coefficient indicates a reduction in number of views, average duration of views per viewer, and subscribers in the month after the event. This is expected and indicates that the Ag Center events and trainings are working effectively to drive the public to the YouTube channel for more information.

Other potential sources of "shocks" are introduced when videos are shared through external sites such as social media or local news outlets. In 2019, a local news site in Ohio linked to the grain bin safety video in an article about a local farmer who was rescued from a grain bin.[15] This video was accessed 791 times in four days through that website, and its viewers were likely a new audience for the Ag Centers' channel. After this initial spike in views, the video was also more likely to appear in other viewers' suggested video feeds as recent views and geography affects the algorithm YouTube uses to suggest videos.[1] After these events, however, there is an inevitable decline in number of views as the story becomes "old news" as indicated by the negative coefficient in the time series.

Despite the fact that the health videos are not viewed as often as the safety and livestock handling videos, the consistent growth in health views is likely why it is a significant predictor of viewership overall. There were few substantial shocks to views in this category, which may indicate that the health videos are being used more consistently, such as for formal trainings. Health videos with the most views focused primarily on pesticides. This may in part be due to the EPA's Worker Protection Standard that requires pesticide handlers and agricultural workers who grow or harvest plants on farms or in greenhouses, nurseries, or forests to have annual pesticide safety handling training.[16] Because regulatory compliance is a primary concern of agricultural employers, such training may be especially relevant and useful to the industry.[17]

Videos used for trainings may have more views than those recorded in YouTube metrics because workers may watch the videos in group settings. The top traffic source for health videos was external sites, accounting for 26.4% of views in this category. Google searches were the most common external source, but unlike the other categories, traffic to health videos also came from multiple education websites (e.g., learning.com, .edu sites for various universities). Traffic from these sources support the view that the health videos are used for training more broadly than the safety and livestock handling videos.

Safety and livestock handling videos may be used in trainings and viewed by groups, but the analytics indicated different top traffic sources for these categories. Safety trainings were most commonly accessed as suggested videos, which YouTube's algorithm concludes are topically related to current videos that users are viewing. Safety videos are more likely to be related to similar videos on YouTube. For instance, videos on ATV safety would be considered topically related to any video with ATVs featured whether they are promotional, recreational, or educational. Such connections provide greater opportunities for videos to be suggested to new viewers. Adding additional keywords and thinking about potential related videos may help increase the likelihood of YouTube suggesting the videos from the Ag Centers' channel. Livestock handling videos were most commonly accessed through YouTube searches suggesting viewers are deliberately seeking out specific content. The most common search terms for livestock handling were "animal care", "milking", "la vaca", "lecherias", and "la lecheria". The fact that three of the top search terms were in Spanish reinforces the need for the Ag Centers to provide health and safety information in Spanish and other languages. It also highlights the importance of culturally and linguistically appropriate content that corresponds to the education and experience level of workers.[5]

Total views showed seasonality in the moving average component indicating that there was a seasonal response to Ag Center events. This could be explained by the fact that the same Ag Center events occur each year at the same time. Viewers appear to access health videos most often in the spring and safety and livestock handling videos most often in the fall. Seasonality trends may be due to the seasonality of agricultural hazards (e.g., pesticide application in the spring and grain storage in the fall). Recognizing when viewers are searching for specific health and safety information could inform the Ag Centers as to what content to produce and when to promote it. The seasonality trends suggest that there are more views and greater watch time hours between March and October with less activity during the winter. In 2019 and 2020, this was more pronounced than in previous years. The peaks align with some of the busiest times in agriculture, which might reflect a need to train more workers or greater attention to health and safety issues at that time. The posting and promoting of new videos might be best if initiated prior to the start of the most likely viewing periods (i.e., adding content during the winter months so it is available in the spring).

The forecast predicts fewer subscribers and the time series analyses indicated negative subscribers at various times. This is likely due to the low level of channel subscribers in general, combined with YouTube's practice of periodically purging subscribers associated with inactive accounts. The low number of subscribers may be partly due to the channel being used for trainings and the wide variety of content. Someone seeking information on livestock handling may not be interested in pesticide application. Also, there is currently no uniform effort by the Ag Centers to encourage viewers to subscribe to the channel. Adding a cue to subscribe at the beginning of each video or creating a collaborative social media campaign to promote subscribing may lead to increased subscribers to the channel over time.

This study had limitations. First, YouTube analytics data may present limitations due to underreporting on some dates, shifting definitions and availability of metrics over time, and restricted access to demographic and geographic data. This may have resulted in inconsistent summing across metrics. Second, this study grouped videos by topic into broad categories (i.e., health, safety, and livestock handling) that may not fully capture nuances between more specific agricultural health and safety topics. Finally, many videos are used to train groups of agricultural workers; however, the data in this analysis cannot account for multiple people viewing the video together on one device.

This study aimed to understand the research questions that can be addressed with YouTube Analytics data and investigated the Ag Center's viewership over time. Future research should continue to explore methods such as time series analysis for evaluating health and safety education and interventions delivered through YouTube. It may be informative to further analyze the U.S. Ag Center's YouTube channel data to understand its viewership more deeply as related to language, seasonality, geographic distribution of viewership, distinct video categories (i.e., biological, chemical, and physical risks, mental health, equipment safety, promotion, etc.), and a combination of these factors. Such analyses may result in meaningful guidance to inform future content for agricultural workers and their families.

Conclusion

YouTube is the most widely used social media platform in rural areas of the country, and the U.S. Ag Centers' YouTube channel is positioned to become a premier repository for quality agricultural safety and health-related videos. This study demonstrated that viewership of the U.S. Ag Center's YouTube channel is growing and that there was seasonal variation in views. In order to continue the observed growth in viewership, the Ag Centers and other agricultural stakeholders should continue to focus on the value of particular content to potential viewers, how and when content is released, and strategic promotion of the channel and its videos.

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- High Plains Intermountain Center for Agricultural Health and Safety (Colorado State University)
- National Children's Center for Rural and Agricultural Health and Safety (National Farm Medicine Center)
- Western Center for Agricultural Health and Safety (University of California, Davis)
- Southeastern Coastal Center for Agricultural Health and Safety (University of Florida)
- Great Plains Center for Agricultural Health (University of Iowa)
- Southeast Center for Agricultural Health and Injury Prevention (University of Kentucky)
- Upper Midwest Agricultural Safety and Health Center (University of Minnesota)
- Central States Center for Agricultural Safety and Health (University of Nebraska Medical Center)
- Southwest Center for Agricultural Health, Injury Prevention and Education (University of Texas Health Science Center at Tyler)
- Pacific Northwest Agricultural Safety and Health Center (University of Washington)

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