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What Minors See on Tiktok: Taxonomy, Prevalence, and Interaction Patterns of Potentially Dangerous Videos

ABSTRACT

Short-form video platforms expose young audiences to algorithmically amplified content, yet systematic, feed-level evidence from TikTok remains scarce. This study analyzes 1,000 TikTok videos collected via a clean, non-interacting 13-year-old profile and classifies each video into one dominant category, recording likes, comments, saves, and shares to map risks and engagement at scale. Entertainment and Arts category predominated overall, with significant between-category differences in all interaction metrics (Kruskal-Wallis), reflecting right-skewed distributions and niche virality patterns. Potentially dangerous content constituted 10.5% of the sample, peaking in Education and Information category (18%), followed by Entertainment and Arts (12.3%) and Lifestyle and Personal Content (10.4%). Domestic SK/CZ videos contained more potentially dangerous content than foreign videos (12.1% vs 7.4%; $\chi^2(1)=5.14$, $p=.023$, $V=0.072$). Potentially dangerous videos received significantly fewer likes and saves than safe videos, while differences in comments and shares were nonsignificant, with a modestly higher median of shares for this content suggesting networked forwarding rather than broad popularity. The leading dangerous subtypes were sexual/sexualized content (26.7%), hate and discrimination (21.9%), and misinformation/manipulation (18.1%). Findings support targeted platform moderation and age-appropriate design alongside media-literacy interventions prioritized for sexualization, hate speech, and misinformation, with attention to locally trending content.

KEY WORDS

Dangerous Videos. Media Literacy. Taxonomic Classification. TikTok. Youth.

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1 Introduction

One of the most popular types of social media content in recent years has been short-form videos. These are short formats lasting from a few seconds to a maximum of a few minutes, which have gained attention mainly due to their wide range of user-generated content. There are several studies that focus on the content of short-form videos, whether in the form of Instagram Reels, YouTube Shorts, or TikTok videos. Ultimately, these are the most visited and popular social media platforms (We Are Social & Meltwater, 2025). In this article, I will focus exclusively on TikTok, as it is one of the most popular platforms among young users (Pew Research Center, 2024). A large part of the studies on TikTok content focus primarily on qualitative analysis of themes and topics selected based on hashtags or popular content related to a specific topic. These include, for example, studies focusing on mental health (Samuel et al., 2024; McCashin & Murphy, 2022), climate change (Basch et al., 2022), tobacco products (Donaldson et al., 2025; Vassey et al., 2022), sex education (Fowler et al., 2021), and education in general (Fiallos et al., 2021). However, significantly fewer studies or reports focus on the content classification of these videos, mainly because it is almost impossible to collect a uniform research sample that would be the same for all users. This is because these social media platforms are governed by personalized algorithms for individual users, so (theoretically) they should never show the same feed to everyone.

TikTok adapts its algorithm to users through any interactions on the platform. This means not only likes, comments, saves, or forwards to other users, but also rewinds, pauses, rewatches, or skips of videos. In short, any interaction that a user performs on the platform. New users thus "train" their own algorithm based on their preferences according to what content they watch and how they interact with it (Siles et al., 2024). At the same time, the algorithm also presents them with videos that have high engagement from other users (Klug et al., 2021). This offers a rather dangerous mix of content loops that users can get caught up in. A high engagement rate can be achieved by a video that is entertaining, educational, or socially important, but also by a video that is "rage bait" and aims to provoke as much discussion and disagreement as possible or deliberately polarize society in order to increase the reach of the post or profile (see, Mathew et al., 2019; Karizat et al., 2021; Rathje et al., 2021). Young users who have not yet developed media literacy or are unable to recognize potentially dangerous content can easily access anything.

The issue is also important because young users and minors, who are the most vulnerable group, spent up to 2 hours a day on TikTok in 2024 (Qustodio, 2024), with this time increasing rapidly every year. Surveys on the distribution of TikTok users most often work with respondents aged 18+ (We Are Social & Meltwater, 2025), so we do not really know how large the user base of children and adolescents is. However, research on children aged 13-17 shows that TikTok is the second most used platform (Pew Research Center, 2024), even though it may promote addictive behavior and psychological distress (Qin et al., 2022; Novanská Škripcová & Viteková, 2025; Li et al., 2022; Lin et al., 2016).

2 Methodology

2.1 Hypothesis and Research Questions Development

The main objective is to examine the content structure, potential risks, and impact of interactions (likes, comments, saves, shares) of videos on TikTok and to determine whether these indicators differ significantly by content category, video origin (domestic/foreign), and the presence of potentially dangerous content.

I aim to achieve this goal at a descriptive level, using relationships between variables and comparisons between individual groups. Based on this, I set the following research questions and hypotheses:

RQ1: What is the representation of videos by content category on TikTok?

RQ2: What are the basic interaction statistics (number of likes, comments, saves, and shares) for individual content categories, and do the numbers of interactions differ between content categories?

- **H1:** There are significant differences in the number of interactions between individual content categories.

RQ3: Does the proportion of potentially dangerous videos differ between content categories, and what is their total proportion in the dataset?

- **H2:** Content category is significantly related to the likelihood that a video will be potentially dangerous.

RQ4: Is the origin of the video (SK/CZ vs. foreign) related to the presence of potentially dangerous content?

- **H3:** Foreign videos have a different proportion of potentially dangerous content than SK/CZ videos.

RQ5: Do interactions differ between potentially dangerous and safe videos?

- **H4:** Potentially dangerous videos receive a different amount of interactions than safe videos.

RQ6: What is the content of potentially dangerous videos?

Following on from RQ1 – RQ6, the content structure of the dataset and the interaction profiles of the videos will first be mapped: proportions will be given for individual categories, and medians and interquartile ranges will be reported for likes, comments, saves, and shares, both overall and by category. Next, the total proportion of potentially dangerous content will be estimated and its distribution among content categories will be described in detail in percentages and absolute numbers. Subsequently, it will be verified whether the probability of potentially dangerous content is related to the content category and, in particular, to the origin of the video (SK/CZ vs. foreign), with the interpretation also indicating the strength of the association, not just statistical significance. In the area of interaction reach, the distribution of metrics will be compared between content categories, between potentially dangerous and safe videos, and between domestic and foreign content; the results will be systematically supplemented with appropriate effect sizes. At the same time, the relationship between interaction metrics (likes, comments, saves, shares) will be examined, and coefficients and significance will be reported to show which metrics covary the most. Finally, a unified, single-label typology of subcategories of potentially dangerous content will be created and their proportions quantified, thereby accurately identifying the dominant risk areas in the dataset without duplicating items.

2.2 Research Design

To classify video content into individual categories, I primarily drew on "Taxonomic Classification for Web-based Videos" (Song et al., 2010). Although this is an older article, its authors worked on this classification for Google. As it contains a number of potential categories, these were significantly simplified and grouped into six main categories. The main categories were:

1. Entertainment and Arts (comedy, music, dance, performance, film, TV series, games...).
2. Education and Information (tutorials, facts, news, science...).
3. Lifestyle and Personal Content (daily life, fashion, food, travel, personal vlog...).
4. Sports and Fitness (workouts, sports content, health tips...).
5. Business and Commercial Content (ads, product reviews, brands...).
6. Social and Community Content (social issues, community, relationships...).

On top of that, an additional category and more detailed information were recorded for all videos:

- likes, comments, saves, shares;
- potentially dangerous content for minors (e.g., misinformation, bullying, violence, self-harm, discrimination and hate speech, dangerous challenges, sex, prostitution, etc.);
- regional affiliation of videos, which divided videos into domestic (Slovak and Czech languages – these two languages are very similar and the inhabitants of the countries understand each other) and foreign (primarily English and other languages – 8 videos that were in Polish, Russian, Hungarian, Romanian, and French).

2.3 Sampling Procedure

In order to ensure the most objective research sample of videos on TikTok, several steps had to be taken. First, a new email address was created at Gmail.com, which was not linked to any other email address and did not contain any information about the user. This email address was then used to register on TikTok. Since the condition for creating an account is to provide your age and the minimum age for using the platform is 13, the date of birth was set to August 15, 2012. No interest categories were selected and no additional information was provided. The account connected to the platform using the Microsoft Edge web browser, which deleted all cookies, history, and preferences stored in the browser after each session. Therefore, the only information TikTok had was the IP address, located in Slovakia. Throughout the data collection process, this account did not interact with any content – it did not like, comment, save, or forward any video to another user, nor did it click on the comments section or user profile. No video was paused, rewound, or rewatched during the entire study, all with the aim of maintaining the profile as "clean" as possible, one that has no preferences and can provide the best possible idea of the platform's algorithm and the videos that TikTok itself recommends.

2.4 Research Sample

Data collection took place from August 20, 2025, to September 12, 2025, always at approximately the same time – around 5:00 p.m. The total sample consisted of 1,000 videos, which were classified into individual categories based on their dominant content focus while being watched. At the same time, a screenshot was taken so that after viewing, it would be possible to record the reach of these videos, or so that I could return to them from another TikTok profile and watch them again if needed. This method was also used to check whether any videos were displayed twice, so as not to distort the results. Duplicates were, of course, removed from the research sample and replaced with the following video. Live streams were also not included in the research sample due to their scope and nature and were the only content that I scrolled past.

2.5 Measurement

Content classification took place during data collection, based on the dominant idea and processing of the video, as described in the Research design. No program was used for data collection and classification; both were done manually by the author of this text. In the case of Business and Commercial Content category, videos that were predominantly sketches, for example, but presented a main idea related to a specific product or service at the end of the video, were also included in this category. I believe that without commercial overlap, these videos would not have been created. During the research, only one content category was reclassified, namely

tutorials on video editing in the CapCut app. I originally classified them as educational content, but this app is owned by ByteDance, which also owns TikTok itself. It is therefore logical that they are promoting themselves and that the basic premise is potential commercial interest (the CapCut app is partially paid). In addition, all of these videos were created in the same way, with the same visuals and identical robotic voices, so they were not authentic videos from different users that want to educate others.

For the analysis and evaluation of results I used descriptive analysis (means, medians), Pearson's chi-square test with Cramér's V calculation (effect sizes), Kruskal-Wallis test with epsilonsquared ε^2 calculation as the effect size (a nonparametric alternative to oneway ANOVA for betweengroup comparisons), and the Mann-Whitney U test with Cohen's D calculation (effect sizes).

The limitation of numerical data in likes, comments, saves, and shares is rounding, which TikTok does automatically for high values.

3 Results

3.1 Representation of Videos by Content Category

To begin with, I will summarize the percentage distribution of taxonomic categories for the entire dataset of videos and for the domestic (SK/CZ) subset in order to compare the content structure across both sets (Figure 1). All videos were assigned exclusively to one category based on the dominant idea or theme (single-label); due to rounding, the totals may differ slightly from 100%. Entertainment and Arts category significantly predominates in both datasets, followed by Lifestyle and Personal content. The SK/CZ subset has a relatively higher proportion of Education and Information videos and a lower proportion of Business and Commercial Content, while other categories remain in the minority. This is an expected result, as TikTok is a platform designed for entertainment, where the audience seeks relaxation and release, to which content creators adapt and create videos that are in demand.

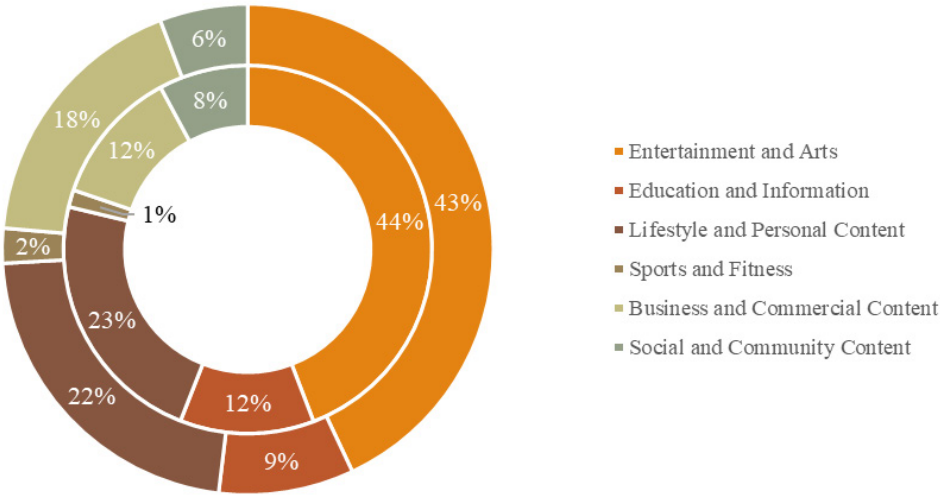

Figure 1: *Percentage distribution of taxonomic categories in the total dataset (n=1,000) and SK/CZ subset (n=663)*
Source: own processing, 2025

3.2 Interaction Statistics for Content Categories and Interactions between Categories

Category	N	Likes		Comments		Saves		Shares	
		M	Md	M	Md	M	Md	M	Md
Entertainment and Arts	430	264,020	21,350	2,223	198	21,005	2,138	18,180	2,017
Education and Information	89	66,519	9,134	823	147	7,372	1,133	6,542	463
Lifestyle and Personal Content	222	335,451	45,300	1,988	425	19,148	3,057	34,432	1,346
Sports and Fitness	23	194,951	67,100	782	259	12,541	3,963	6,404	1,467
Business and Commercial Content	178	70,936	10,900	863	138	12,024	2,582	6,918	485
Social and Community Content	58	270,944	14,650	2,586	186	15,419	1,684	8,222	686

Table 1: *Descriptive statistics of the total dataset (n=1,000)*

Source: own processing, 2025

Kruskal-Wallis tests confirmed statistically significant differences between content categories in the number of likes ($\chi^2(5) = 46.3$, $p < .001$, $\varepsilon^2 = 0.046$), comments ($\chi^2(5) = 29.2$, $p < .001$, $\varepsilon^2 = 0.029$), saves ($\chi^2(5) = 15.3$, $p = .009$, $\varepsilon^2 = 0.015$), and shares ($\chi^2(5) = 56.1$, $p < .001$, $\varepsilon^2 = 0.056$). The effect sizes were mostly small (likes, comments, saves), while sharing achieved an effect approaching medium strength.

In all categories, the means are significantly higher than the medians, indicating right-skewed distribution and the presence of very popular videos with high reach. However, these are mainly found in foreign content. If we consider only domestic videos subset, the standard deviations for likes decrease dramatically, indicating less influence from extremes, less right-skewed distribution, and lower average values (Table 2).

The overall dataset shows that the Sports and Fitness category achieves the highest number of likes, despite its small representation (only 2% of content in terms of taxonomic classification). Most of these videos dealt with popular sports (especially soccer), indicating the presence of a strong fan base for this sport. The Lifestyle and Personal Content category has the most comments, which indicates extensive audience discussions in this section and the expression of personal opinions. Sports and Fitness again dominates in terms of saves, and shares were highest in the Entertainment and Arts category, indicating an effort to share this content with friends. In the overall dataset, Sports and Fitness is therefore the most successful category in terms of interactions. However, when interpreting these results, it is necessary to take into account the very uneven representation of individual categories in the dataset, as Sports and Fitness account for only 1-2% of all videos.

Category	N	Likes		Comments		Saves		Shares	
		M	Md	M	Md	M	Md	M	Md
Entertainment and Arts	293	23,421	12,200	239	105	2,868	1,285	3,454	1,253
Education and Information	78	17,030	7,346	261	128	2,871	902	2,065	421
Lifestyle and Personal Content	151	40,002	20,000	464	206	2,826	1,124	2,727	737
Sports and Fitness	10	5,927	5,594	44.9	30.5	364	209	143	115
Business and Commercial Content	79	18,743	7,952	240	57.0	2,269	577	1,314	220
Social and Community Content	52	23,072	10,430	485	144	2,738	998	1,842	532

Table 2: *Descriptive statistics of the SK/CZ subset (n=663)*

Source: own processing, 2025

The domestic subset, which – by its nature – does not contain videos with global impact and interactions, shows different results. The Lifestyle and Personal Content category clearly dominates both likes and comments, which may indicate the frequent occurrence of popular content creators – influencers. They often encourage their audience to write their opinions in the comments, thereby increasing the reach of the video, as the algorithm evaluates the video as relevant. In saves and shares, the Entertainment and Arts category ranks first, indicating the audience's desire to return to the video later and repeatedly or discuss it with friends.

3.3 Proportion of Potentially Dangerous Videos among Content Categories and Their Total Share

Potentially dangerous videos account for 10.5% of the total sample n=1,000. These potentially dangerous videos are mainly concentrated in the Entertainment and Arts category (53 out of 430), followed by Lifestyle and Personal Content (23 out of 222) and Education and Information (16 out of 89).

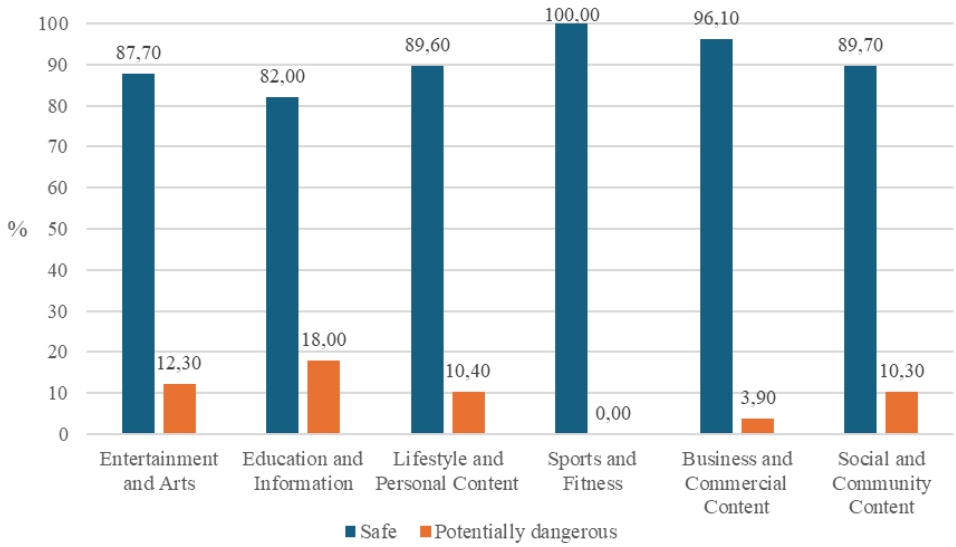

Figure 2: *Distribution of potentially dangerous content across content categories*

Source: own processing, 2025

As shown in Figure 2, the proportion of potentially dangerous content varied across categories. The highest share was observed in Education and Information (18%), followed by Entertainment and Arts (12.3%), Lifestyle and Personal Content (10.4%), and Social and Community Content (10.3%). In contrast, Business and Commercial Content contained only 3.9% of potentially dangerous videos, while Sports and Fitness did not include any. These differences were statistically significant ($\chi^2(5) = 17.7$, $p = .003$, Cramer's V = 0.133), although the strength of association was small.

The distribution of shares among potentially dangerous videos is 50.5% for Entertainment and Arts, 21.9% for Lifestyle and Personal Content, 15.2% for Education and Information, 6.7% for Business and Commercial Content, and 5.7% for Social and Community Content. The only category not represented is Sports and Fitness, which did not contain any potentially dangerous videos.

These results are particularly serious for the Education and Information category, which has the highest share of potentially dangerous content (18%). Given the nature of the category, these are mainly videos that, for example, pretend to be news, reports or give a professional or educational impression, but in terms of content, they mainly involved disinformation, deliberate manipulation, or racial discrimination (e.g., topics about Europe preparing for World War III, the introduction of totalitarianism in Europe, the war in Ukraine, or disinformation about the murder of an American activist or, conversely, approval of this murder). Minors who encounter such content may not have sufficiently developed media literacy to be able to discern the intentions of these creators and can easily fall into a bubble of misinformation, hatred, or fear (note that the TikTok profile was set to an age of only 13). The Entertainment and Arts category featured topics such as bullying, stereotyping and objectification of women, explicit depictions of sex (most often from erotic or directly pornographic films), rape, denigration and ridicule of people with disabilities or other minorities, sexual harassment and its trivialization. Bullying, drug use, and theft appeared in the Lifestyle and Personal Content category in the form of personal stories, but there were also videos that indirectly promoted OnlyFans or other websites providing sexual services or sexual content.

3.4 Relationship between the Origin of the Video (SK/CZ vs. Foreign) and the Presence of Potentially Dangerous Content

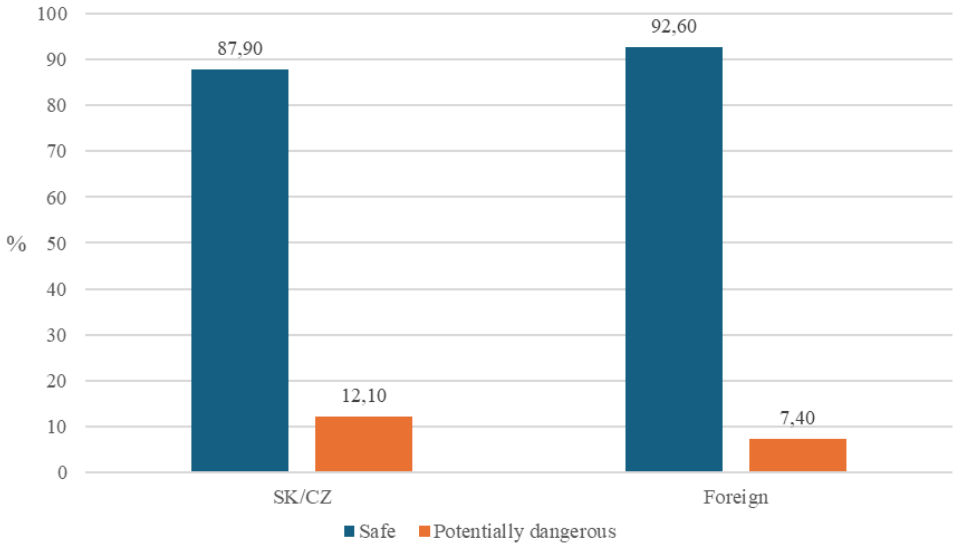

Figure 3: *Distribution of potentially dangerous content in SK/CZ subset (n=663) and foreign subset (n=337)*
Source: own processing, 2025

As illustrated in Figure 3, SK/CZ videos contained a higher proportion of potentially dangerous content (12.1%) compared to foreign videos (7.4%). The χ^2 test of independence confirmed a statistically significant association between video origin and the presence of potentially dangerous content ($\chi^2(1) = 5.14$, $p = .023$, Cramer's V = 0.072), although the effect size was very small.

The difference in the proportion of potentially dangerous content between domestic and foreign videos is clear – 80 potentially dangerous videos (12.1% of 663) were identified in the SK/CZ subset, while only 25 videos (7.4% of 337) were identified in foreign content. The higher proportion of potentially dangerous videos in domestic content may be related to the nature of local trends or the specific style of humor that prevails on the platform. The difference was statistically significant, but the effect size remains very small, which means that in practice this difference is only slight.

3.5 Interactions in Potentially Dangerous and Safe Videos

Category	N	Likes		Comments		Saves		Shares	
		M	Md	M	Md	M	Md	M	Md
Safe	895	243,828	21,000	1,913	213	18,482	2,345	18,941	1,201
Potentially dangerous	105	81,122	11,100	754	132	6,861	1,288	9,014	1,262

Table 3: *Descriptive statistics of interactions in potentially dangerous content in the total dataset*
Source: own processing, 2025

The Mann-Whitney U test showed significant differences in the number of likes ($U = 36{,}968$, $p < .001$, $r = -0.213$) and saves ($U = 38{,}111$, $p = .002$, $r = -0.189$), with small to medium effects. No significant differences between safe and potentially dangerous videos were found in comments ($U = 41{,}647$, $p = .059$, $r = -0.113$) and shares ($U = 43{,}942$, $p = .277$, $r = -0.065$).

In the medians of all interactions except shares, we can see that safe videos predominate. The exception is the aforementioned shares, but this does not necessarily indicate a negative connotation. The higher median for shares may also be due to the basic human tendency to share something with loved ones that they want to enjoy together or to alert each other to "shocking" content. The results suggest that potentially dangerous content, although it may attract attention in some niche groups, generally does not receive more likes, comments, or saves than safe content, which may be directly related to recommendation algorithms or interventions by the platform to limit their reach. Interestingly, the higher median number of shares for dangerous content may reflect an effort to spread this content mainly in closed communities, although in the overall dataset this difference represents only a small segment of interactions.

Category	N	Likes		Comments		Saves		Shares	
		M	Md	M	Md	M	Md	M	Md
Safe	583	25,502	11,400	304	111	2,762	1,058	2,501	666
Potentially dangerous	80	26,289	7,206	350	125	2,574	889	4,098	815

Table 4: *Descriptive statistics of interactions in potentially dangerous content in the SK/CZ subset*
Source: own processing, 2025

The Mann-Whitney U test showed that the number of likes was significantly higher for safe content ($U = 19{,}198$, $p = .010$, mean difference = 2,701), with a small to medium effect (rank biserial correlation $r = -0.177$). For comments ($U = 23{,}041$, $p = .882$, $r = 0.010$), saves ($U = 20{,}677$, $p = .100$, $r = -0.113$) and shares ($U = 22{,}784$, $p = .739$, $r = 0.023$), no statistically significant differences were found, with negligible effect sizes.

The results thus indicate a change from the aggregated analysis of the entire dataset (without distinguishing the origin of the video), where there was a difference between safe and unsafe content in the number of likes and saves. However, after separating only the domestic subset, the differences in saves and other metrics disappeared or lost significance, while the direction of the effect did not reverse. This phenomenon reflects the nature of Simpson's paradox: the overall data may suggest a stronger or more significant effect than the analysis within a more homogeneous subgroup, where the differences between groups are not as pronounced.

3.6 Content of Potentially Dangerous Videos

The largest group consists of videos with sexual content, including explicit depictions of sexual intercourse, objectification of women, and references to paid sexual services (28 out of 105; 26.7%), followed by hateful and discriminatory content, including racism, sexism, and misogyny (23; 21.9%) and misinformation/manipulation (19; 18.1%). Next in line are bullying and harassment, including cyberbullying, ridicule, and humiliation (16; 15.2%). Smaller but significant in terms of risk are groups related to substance abuse (7; 6.7%), dangerous challenges with the potential for direct harm to health (6; 5.7%), and violence/abuse, including fights and rape (6; 5.7%).

The classification was carried out as a single-label based on the dominant theme of each video; the dangerous challenges category was classified separately to highlight cases with a direct safety risk. In the context of the previous finding on differences between content categories and the higher proportion of potentially dangerous videos in the domestic subset, these results suggest three dominant risk areas on the platform: sexualization/commercialization of the body, hateful and stereotypical expressions, and misinformation. In practical terms, this supports the need for targeted moderation and media education interventions, particularly in these three areas, with special attention also required for challenges with a direct security impact on young audiences or minors.

4 Discussion

Despite the fact that TikTok is one of the dominant social media platforms among young people and we have long suspected that its content may also be potentially dangerous, the academic sphere in the field of media studies has significantly underestimated it in terms of research. For several years now, psychology, psychiatry, neurology, and other fields have focused on its impact on individuals, but the content of the platform itself remains under-researched. The research presented here provides only a small fraction of the content that young people may encounter and that shapes their opinions and beliefs through the long hours (Qustodio, 2024) they spend on the platform every day.

The dominant risk areas – sexualization, hate speech, and misinformation – are maintained in short video formats for several reasons. They are inexpensive to produce, easy to spread, and achieve relatively high interaction, which can also bring financial gain or other benefits. Even if other users try to point out misinformation in the comments and warn others, they only increase the video's engagement from the algorithm's point of view, and the algorithm recommends it to other users. It is therefore a "vicious circle" that can only be effectively stopped by the platform itself.

In the previous section, I described the interaction profile of individual content categories and the significance of effect sizes. However, these cannot sufficiently capture the actual significance and potential impact that dangerous videos can have. While videos depicting stereotypes, bullying, or racism may have long-term consequences and influence the formation of an individual's values, a single video with a dangerous challenge can have almost immediate negative consequences for the health or life of young people and minors if they decide to replicate it (see, Al Hassan et al., 2024; Feijoo et al., 2023; Ataga & Arnold, 2025).

TikTok officially prohibits several areas of content in its Community Guidelines, including hate speech and hateful behavior, violent and hateful organizations and individuals, harassment and bullying, dangerous activity and challenges, body exposure and sexualized behaviors, shocking and graphic content, and misinformation (TikTok, n.d.). Nevertheless, such potentially dangerous videos accounted for 10.5% of the total dataset. Although the platform states that it deletes inappropriate content or applies age-restrict filters to it, it does not do so quickly or effectively enough. Many of the potentially dangerous videos were serious violations of the Community

Guidelines, which are not suitable even for sensitive adults, let alone minors (for example the footage of two violent murders, who were shown without filters or blurring, accompanied by extreme hate speech and racist slurs). The fictitious profile I used to conduct my research was set to be only 13 years old, which is the minimum age requirement for registering a profile on the platform.

Of course, the research can only be generalized to a certain extent and has several limitations. Generalizability was ensured by a clean profile with no preferences, linked to a clean email address and a clean internet browser with no cookies or history, and the profile did not interact with content in any way during the entire research. Daily variability was thus only influenced by session-dependent information and videos viewed in the history of the given profile. This was reflected in several cases of duplicates, which were removed from the dataset (a total of 17 duplicates during the entire research period). When interpreting the results, it is taken into account that the interaction metrics have skewed distributions and unequal group sizes; therefore, non-parametric comparisons and effect sizes are key, not just p-values. Relationships between categorical variables are evaluated together with the measure of association strength (Cramér V) to avoid overestimating statistical significance alone. Another limitation is the geolocation of the IP address, which was in Slovakia and therefore logically carries a linguistic and cultural bias. Specific and not very widespread languages, such as Slovak, carry with them a significant influx of videos in the related Czech language and the presence of the global English language. Only a negligible number of videos were in languages other than these. For this reason, videos in Slovak and Czech were coded as domestic and others as foreign. Given the fixed time window of collection and the "clean" profile, it is advisable to read the results with caution and motivate replications with multiple seed profiles, for which, however, it will be necessary to ensure cross-elimination of duplicates. There is potential for further research also in longitudinal replication due to the seasonality of trends and the sensitivity of content to global events, but also in research with multi-label analysis or network aspects of dissemination that could track the amplification of specific content.

The implications of this research for practice are more than obvious. Current platform filters are unable to prevent the uploading and dissemination of content that could be considered potentially dangerous for young audiences and minors. Although security policies at the European Union level, as well as in other countries, have long sought to increase the protection of minors in the digital environment (European Commission, 2023, n.d.a, n.d.b), they still lag behind the development of social media like TikTok. Media education and increasing the media literacy of young people therefore remain a relevant "barrier" and protection against potentially dangerous content. Parents, teachers, science popularizers, leisure activity leaders, and others undoubtedly have a role to play in this process.

5 Conclusion

This study successfully mapped 1,000 TikTok videos that were collected as the purest possible videos dataset, unaffected by the algorithm of individual user interactions. These are videos that the platform's algorithm recommends on its own. Taxonomic content categorization was applied to these videos using single-label content categories, and interaction metrics for individual videos were collected, allowing for clear comparisons across content categories. In both the overall and domestic subsets, Entertainment and Arts is the most represented category (43% and 44%), followed by Lifestyle and Personal Content (22% and 23%), Business and Commercial Content (18% and 12%), and Education and Information (9% and 12%). In terms of interactions, the strongest categories are as follows: Sports and Fitness dominates in likes, Lifestyle and Personal Content in comments, Sports and Fitness again in Saves, and Entertainment and Arts in shares. In the domestic subset, Lifestyle and Personal Content dominates in likes and comments, while Entertainment and Arts dominates in saves and shares.

Another important part of the research was videos that are potentially dangerous for minors (the fictional TikTok profile that collected the dataset was set to be only 13 years old). Differences in the probability of potentially dangerous content occurring were found between content categories, which supports more targeted moderation by genre/theme. The total share of potentially dangerous videos was 10.5% across the entire dataset. Proportionally, these dangerous videos were most prevalent in the Education and Information category, at 18%. The origin of the video (SK/CZ vs. foreign) is related to the presence of risky content, which indicates the role of local norms and language bubbles (12.1% for the domestic subset and 7.4% for the foreign subset). The reach of interactions varies between categories; interpretation is based on media and effect sizes, not just p-values, which reinforces the factual significance of the findings. Potentially dangerous videos do not show a uniform "boost" across all metrics; differences between interaction types confirm that engagement is multidimensional and may not reflect content quality or safety. Correlation analysis between metrics shows that metrics behave differently; shares may also indicate network dissemination alerting to shocking content, not necessarily popularity. The single-label typology of risk subcategories identifies three areas most relevant to practice (sexualization/commercialization of the body, hate speech and discrimination, misinformation) that should be prioritized in moderation and media education. From a methodological point of view, the work provides a replicable framework: a dominant theme per video, comparisons using non-parametric methods, and an emphasis on effect sizes for transparent interpretation. Limitations (single time window, "clean" profile, local language context) motivate replication in multiple waves and with multiple seed profiles, or possibly extension to multi-label and network dissemination analyses.

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