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Visualizing Content-based Categorization of Social Media Platforms: A Study of UK Users

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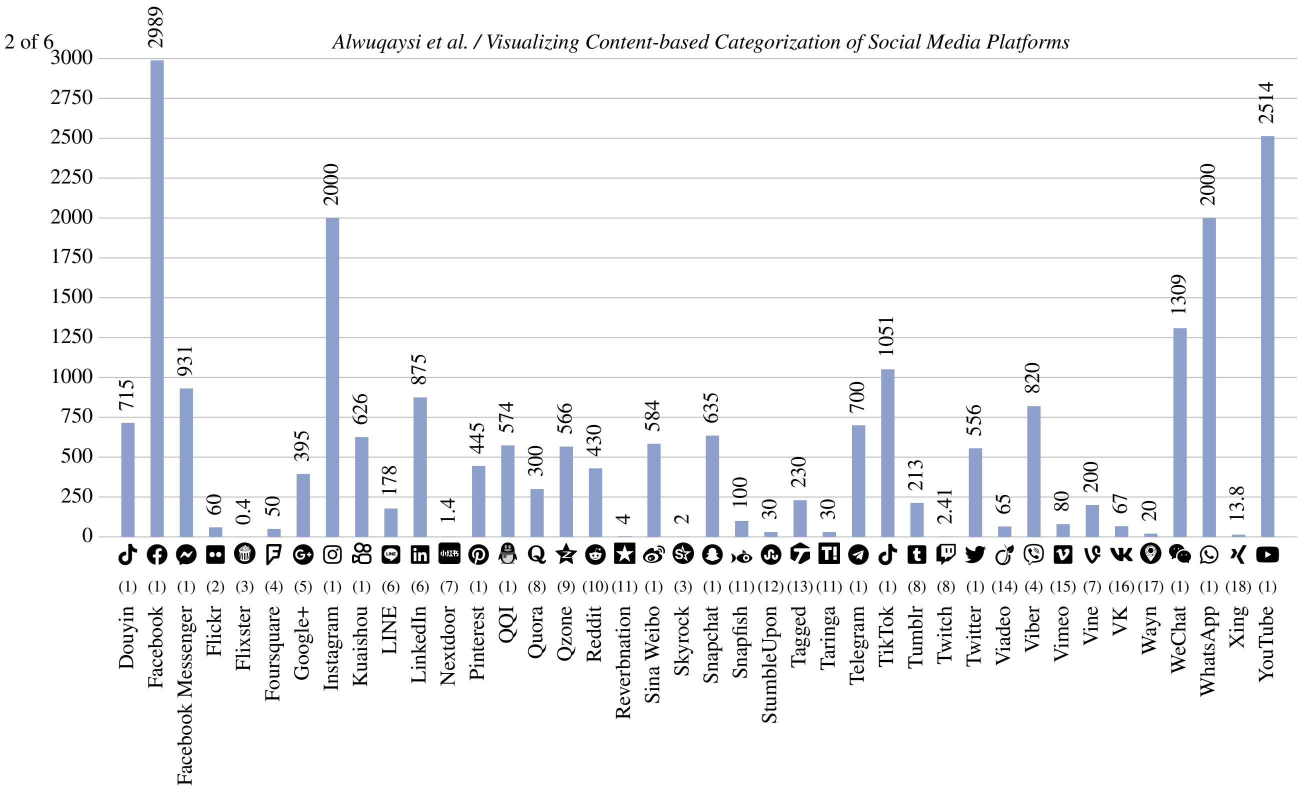
Abstract
In this work, we present the first stage of our ongoing research aimed at visualizing the content-based categorization for social media (SM) platforms to understand how users utilize them. Different content types attract distinct audiences with unique expectations. This can help categorize platforms based on user demands and interests, benefiting researchers, marketers, and individuals seeking to use SM effectively. We surveyed 194 social media users, primarily focusing on those from the United Kingdom, who comprised 76.29% of the sample in 2023. We ask users to categorize the most commonly used SM platforms by choosing from the following categories, image-based, text-based, image-text, and not familiar, aiming to capture the dynamic nature of user content-based interactions. Our findings suggest that users categorize social media based on their usage patterns, regardless of intended purpose. Our next step is to study how usage varies across demographics and impacts individuals.

CCS Concepts
• ***Human-centered computing*** → ***Social networks; Information visualization;***

1. Introduction and Related Work

Social media platforms have become an essential part of our everyday lives, making it important to understand how users interact with these platforms. The impact of SM usage varies based on the type of platform and the demographic characteristics of the users [LZ20]. Users interact with SM in various ways, as mentioned by [EVGL14], and as social platforms keep evolving with new features, we can see that they are becoming more alike [GH13]. This convergence is driven by a concerted effort to enhance their usage and popularity [VD13]. Several studies have significantly advanced our understanding of social media platforms. For instance, [BGZ*22] explored user engagement dynamics, [HLW*22] examined algorithmic curation, [HLZ*20] investigated social media's impact on public opinion formation, and [BAB*18] analyzed echo chambers. These studies provide insights into user behavior, content dynamics, and the broader social implications of social media platforms, laying the groundwork for our research. Additionally, further studies have contributed to our comprehension of the progress in SM research and its consequential implications.For instance, [CHHH20] analyzed social media's influence on consumer behavior and highlighted shifts in purchasing patterns. [SAB21] explored the ethical implications of data privacy on social media, emphasizing the need for regulatory frameworks. [HLZ*20] identified links between prolonged social media use and mental health issues. [Kul18] illustrated the role of social media in crisis communication, emphasizing its effectiveness in emergency response. [LFS16] analyzed the evolution of social media algorithms and their impact on information diversity. These studies collectively enhance our understanding of social media's impact, highlighting key areas of influence and ongoing challenges in the field. Nevertheless, categorizing these platforms from the users' perspective has been overlooked [SŽ23]. Categorization is crucial for understanding user preferences, enabling effective marketing strategies, and predicting platform-switching behaviour [Zho21, WHT16, TLHL19]. Furthermore, visualizing the categorization of social media platforms improves understanding of popular trends in social networks [LZR21]. Available research concentrates on how users utilize and perceive platforms but frequently neglects how users classify SM platforms [WHT16]. Thus, more research is essential to understand user preferences and behaviours, as this insight can contribute to a more effective categorization of platforms [NY16, JB22]. Understanding how users utilize SM is crucial when studying its effects on individuals [RMM*23, dV23]. This paper presents an initial step of ongoing research to develop and visualise a content-based categorization of SM platforms. Our primary objective is to examine how users from diverse demographic groups (i.e., United Kingdom users) categorize SM platform types based on usage patterns. This investigation will shed light on dynamic and continually evolving user interactions when categorizing SM platforms. By understanding how users engage with the various content types offered by SM platforms, we aim to provide valuable insights into the unique dynamics of SM usage and its associated impacts. Furthermore, as part of our future research, we plan to broaden our demographic scope, encompassing a more extensive range of user demographics. Our ultimate goal is to understand better how different SM platforms influence individuals' well-being and how these effects may vary based on users' demographic characteristics.

Our Contribution. Users' content sharing on SM is a dynamic and multifaceted process that can be influenced by users' usage preferences and the nature of the platform itself. For example, a user may prefer Instagram to share images, whereas Twitter to consume text posts. We thus broadly categorize SM into four main types: image-based social media, which focuses on images and videos; text-based social media, which relies on written content; and image-text social media, which can be used for both and unfamiliar with this platform. We collected a sample of 194 SM users in 2023 to do this. We asked them to categorize the most commonly used SM platforms (e.g., Twitter, Instagram, and Snapchat) from their perspective and based on their usage patterns we visualise it. We have observed that individuals frequently create content on their respective SM accounts, and their usage patterns exhibit varia-



(1) [Sta24] (2) [Bro24] (3) [Sim24] (4) [Gaj24] (5) [Sto24] (6) [Bus24] (7) [Fra24] (8) [Sag24] (9) [Tri24] (10) [Dea24] (11) [Ram24] (12) [Tra24] (13) [Ear24] (14) [Min24] (15) [Lem24] (16) [Hou24] (17) [WAY24] (18) [Xin24]

Figure 1: *Monthly Active SM Usage Worldwide in Millions.*

tions across different platforms. This study will further our broader project, which aims to comprehensively understand how users interact with social media and share/consume content.

2. Methodology

Data for this study was collected online using the Social Media Categorization survey (Click here to see the survey details used in this study). We surveyed 194 participants in 2023. In January 2023, 36 of the most-used SM platforms worldwide were included in the survey's first round with 91 participants. In December 2023, a second survey round was conducted to update the platform list and validate the findings with 103 participants. Additional platforms were included to keep up with the latest developments. 41 globally prominent SM platforms were presented to participants. The latest monthly active SM users worldwide in millions is displayed in Figure 1, which depicts all the SM platforms listed in both rounds as the most popular globally (e.g., Facebook, YouTube, Instagram). Five additional platforms emerged and were rapidly adopted between the two rounds, as shown in Figure 3. The survey included demographic questions and a list of popular global SM platforms, and participants were asked to categorize each platform based on their content-sharing/consummation preferences; Figure 2 illustrates the categorization process. To ensure a fair distribution of responses, randomization has been used to reduce any potential response bias [AHR*23].

Content-based Categorization. Participants were asked to categorize SM platforms based on their consumption patterns: image-based SM (IBS), text-based SM (TBS), both text and image-based SM (Both), or not familiar with the platform (Not Familiar). This categorization was created for this study based on SM platform usage. Understanding the diverse world of online communication and its implications increasingly depends on categorizing SM platforms based on user behaviour. Different content on SM can have different effects. For example, text-based content could lead to problems like stress and mental health issues [Hua23], while image-based SM can positively affect well-being [dV23]. However, individual characteristics and cultural context play a significant role, emphasizing the need to consider content specifics for a comprehensive understanding [Med23, Sin23].

Pilot Testing. Four participants participated in a pilot test to assess the initial survey. User feedback was collected to identify potential problems. As part of this iterative process, we made adjustments that improved the study's readability and validity.

Statistical Analysis. Statistical analysis was performed using SPSS 28 and AMOS 24.0, presenting categorical data as frequencies and percentages. A significance level of $P < 0.05$ (two-tailed) was considered statistically significant. Linear regression analysis of the relationship between frequencies and percentages for SM categorization in the two rounds revealed a no-significant correlation $P > 0.05$ when compared with other independent variables such as age, gender, country, and discipline. An example of this analysis is illustrated in Table 1 which represents a sample of the minimum values found in the linear regression analysis for SM classification frequencies and percentages (Click here to see the extended table).

Sample Description. Recruitment for Social Media Categorization online survey was performed through various online SM platforms and the UK-based university official website (Anonymized for submission requirements). The contribution to this study was anonymous and voluntary, with informed consent obtained from

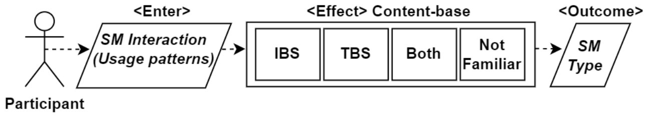


Figure 2: *SM Categorization Based on User Usage Patterns.*

Table 1: *SM Minimum Values Sample for Linear Regression Analysis for All Rounds.*

Social Media Platforms	95% CI	*P* value
Douyin	−0.1654 – 3.9675	0.052
Foursquare	−0.2134 – 0.9870	0.130
Instagram	−0.7135 – 8.1295	0.354
Kuaishou	−0.7391 – 6.0887	0.093
Nextdoor	−0.0858 – 7.5354	0.239
Pinterest	−0.8671 – 8.6598	0.143
Qzone	−0.6481 – 7.4861	0.163
Reddit	−0.9682 – 4.3059	0.359
Reverbnation	−0.4243 – 1.6543	0.131
Snapfish	−0.9781 – 6.9851	0.111
StumbleUpon	−0.6978 – 5.6758	0.237
Viadeo	−0.5871 – 4.5741	0.139
WeChat	−0.6705 – 2.3961	0.323
YouTube	−0.9401 – 3.7861	0.165

CI: Confidence interval, Statistical significance at P-value < 0.05

all participants before completing the survey. A total of 194 participants were surveyed, with 91 participants in round 1 and 103 participants in round 2. 148 participants were from the UK, making up 76.29% of the sample and 23.71% from other countries. In round 1, there were 76.4% from the UK and 23.6% from different countries. As of round 2, 76.2% of participants were from the UK, while 23.7% were from other countries. The analysis reveals the characteristics of the study participants. In round 1, round 2, and overall rounds, most participants were predominantly young, with 89.9%, 82.9%, and 86.1% of participants being under 45 years old, respectively. The survey participants ranged in age from 18 to 75 years (mean age: 24.6 years). Regarding gender distribution, 57.3% of the total sample were females, 40.7% were Males, females accounted for 61.8% and males for 36.0% in round 1, while in round 2, females represented 57.1% and males accounted for 40.0%. Regarding participants' majors or fields of work, the top categories were Education 14.1%, Psychology 10.0%, Business, Management, Marketing, and Related Support Services 8.1%, and Social Sciences 8.1%.

Ethics. The Social Media Categorization survey was granted ethics approval by the researcher's UK-based University Research Ethics Committee.

3. Results

Our results revealed an overall tendency among individuals to engage in content creation on their SM accounts actively, exhibiting substantial variations in their consumption patterns across distinct platforms. The visualization of categorising the 36 most used SM in round 1 vs. the 41 most used SM in round 2 is presented in Figure 3. Notably, the disparity in 5 platforms between the two rounds is visually represented by empty bars in round 1 (e.g., Douyin, Quora, and Tagged). In contrast, round 2 features a complete set of bars indicating the inclusion of newly added platforms. Participants frequently contribute content to their accounts, and their consumption habits vary across different platforms. Visualizing the total categorization of SM across all rounds from UK users' perspectives is represented in Table 2 that encompasses 8 platforms, including Flickr, Instagram, Pinterest, Snapchat, TikTok, Tumblr, Vimeo, and YouTube under the category (IBS), 7 platforms including Facebook Messenger, LinkedIn, Quora, Reddit, Telegram, Twitter, and WhatsApp under the category (TBS). At the same time, Facebook is the only platform under the category (Both), and the remaining 24 platforms are categorized as (Not familiar). Users choose SM categories that often match the platforms' planned design purposes. For instance, Instagram and Snapchat are consumed as IBS, while Twitter and WhatsApp are consumed as TBS. However, in some cases, like Tumblr and LINE, the match between the SM category and the platform's planned purpose is unclear.

4. Discussion

In Table 2, we present visualizing the categorization of SM platforms from the UK users' perspective for all rounds. The perspectives of users' usage patterns on the SM categorization presented in this table shed light on the contribution of SM categorization in this particular demographic. Moreover, it is essential to note that a significant proportion of Asian-based platforms [Dig23] were placed in the (Not familiar) category. As a result, we can understand how UK users are positioned within global patterns of SM consumption when we work on future research that will consider additional countries and compare it to global SM patterns [BS12]. This finding encourages the exploration of broader demographic studies when investigating SM platforms. We investigate the effect of the tested demographic characteristics (e.g., age, gender, and discipline) on the categorization process. Our findings indicate that most participants were young (mean age: 24.6 years), highlighting the younger generation's influence in SM categorization [Sin23]. The high percentage of participants under 45 suggests that SM categorization is a subject of interest primarily for this age group [Whi19]. Gender distribution revealed a slightly higher representation of females (57.3% of the total sample were females, 40.7% were Males), which could imply potential differences in their perspectives and usage patterns [SPC*21, PT22]. The significant increase in the number of participants from the UK (76.29%) indicates a higher level of UK representation [AMA*22], as the survey was distributed in a UK-based university, which influenced the perspectives on SM categorization from the UK participants' perspectives. The present paper primarily focuses on UK users, as most of our study sample originates from this region. The choice to emphasize the UK is warranted considering the latest statistics, which indicate a high SM penetration rate of 90.02% among the population [Sta24]. Furthermore, as of January 2023, the UK boasts a substantial user base of 57.1 million active SM users. These figures highlight the relevance and importance of examining SM usage patterns and their impact within the UK setting. According to participants, Education, Psychology, Business, Management, Marketing, and Social Sciences are the most prevalent fields of work, reflecting the diversity of professional backgrounds and their potential impact on SM categorization. It is important to note that this diversity is preferable as we categorize SM to study how different categorizations of SM platforms' impact can vary in different fields of work [PS22]. Figure 3 visually represents the dynamic evolution in the number of categorized SM platforms over the two data collection rounds. It should be noted that round 2 witnessed the ad-

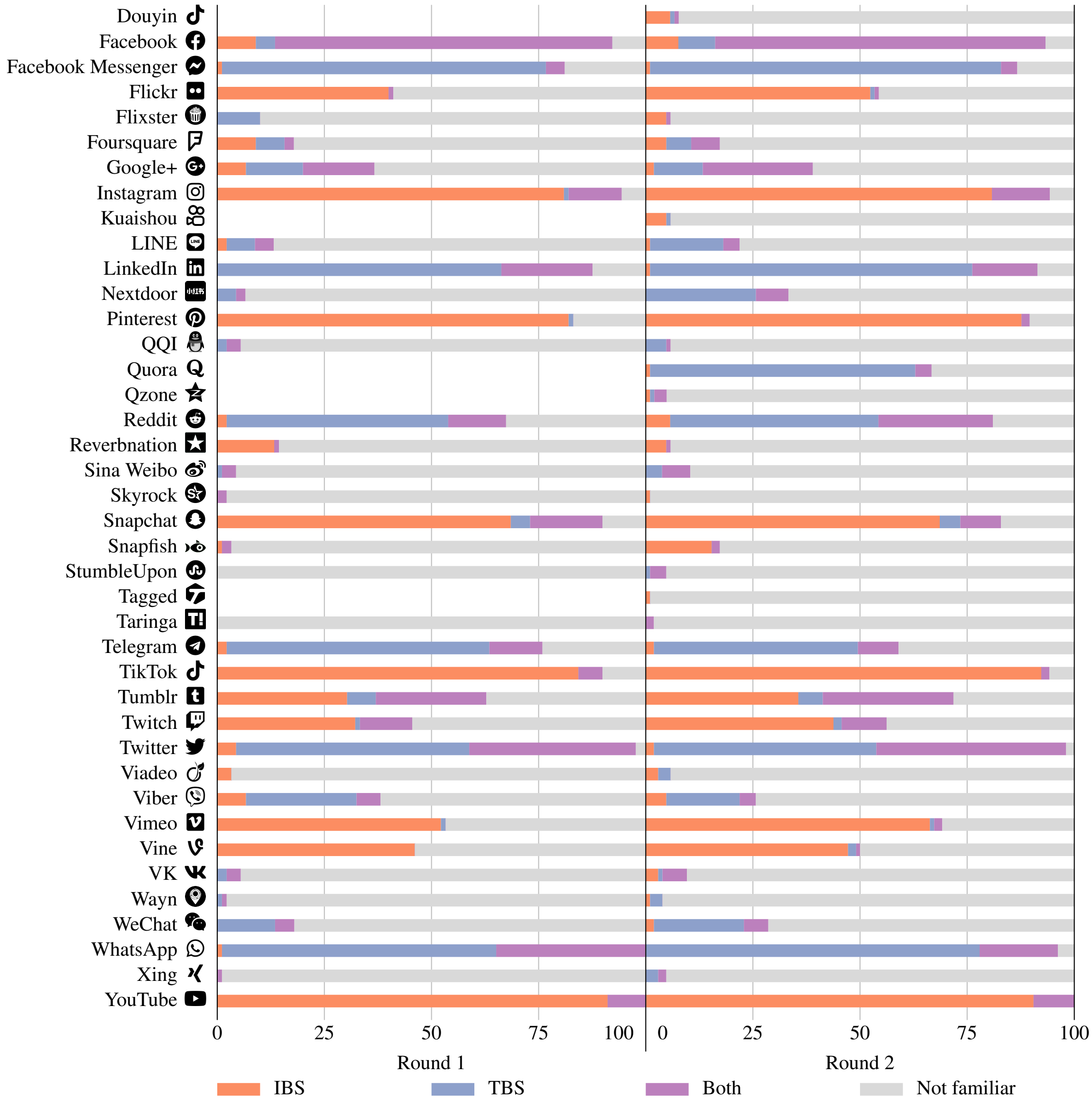


Figure 3: *Visualizing the Comparison of SM Categorization Frequencies: Round 1 vs. Round 2.*

Table 2: *Visualizing the Total Categorization of SM Across All Rounds.*

IBS	TBS	Both	Not familiar			
Flickr Instagram Pinterest Snapchat TikTok Tumblr Vimeo YouTube	Facebook Messenger LinkedIn Quora Reddit Telegram Twitter WhatsApp	Facebook	Douyin Flixster Foursquare Google+ Kuaishou LINE	Nextdoor QQI Qzone Reverbnation Sina Weibo Skyrock	Snapfish StumbleUpon Tagged Taringa Twitch VK	Viadeo Viber Vine Wayn WeChat Xing

dition of new platforms, highlighting the ever-changing nature of SM and the need to adapt categorization methods to accommodate them. We discovered that individuals frequently contribute content to their accounts, and their consumption habits vary significantly across different platforms.

5. Limitations and Implications

Our current research focuses on visually categorizing content on social media platforms and understanding the dynamics of sharing online information. Categorizing SM based on content can be more effective than other methods [MAH22] because it is more adaptable to changing user behaviours and evolving platform trends, allowing for dynamic and up-to-date analysis of user engagement and content. It proves advantageous in identifying how users mould the use of a platform, even when it strays from the platform's original intent, thereby offering a more genuine portrayal of SM usage. While our work has been primarily based on a UK sample, limiting its generalizability, we recognize the need for future research to explore its applicability to a broader context. Future studies should diversify samples and explore how users from diverse demographics categorize SM platform types based on usage patterns. Further research should also consider platform features and categorization processes in its investigation. Despite its limitations, this research has implications for SM professionals, policymakers, and researchers. Customizing platforms to user preferences enhances the user experience, benefiting content creators, researchers, and marketers [BZG*14, RHB*18, Kul18]. Understanding user behaviour enables targeted campaigns and media bias analysis, improving various aspects of SM, including user experience, content creation, research, marketing, and media analysis.

6. Conclusions

This research aims to visualise and understand how users categorize SM platforms according to usage patterns. It reveals that users often categorize platforms according to their preferences, emphasizing the dynamic nature of user interactions. Future research will explore the impact of demographics on these patterns, contributing to a broader understanding of SM usage dynamics.

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