HEC MONTRÉAL

S'élever au-dessus de la mêlée : comment le contenu généré par les organisations sportives influence l'engagement des utilisateurs sur les médias sociaux ?

Rising above the fray : How does content generated by sports organizations influence user engagement on social media ?

par
Caroline Chaussegros de Léry

Sciences de la gestion
M. Sc. Marketing

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Sommaire

Les réseaux sociaux ont transformé les communications et le monde des affaires (Edosomwan et al., 2011). Alors que 58 % de la population mondiale les fréquentent, une part croissante du budget média des entreprises y est investie (Drenik, 2021 ; Harris Poll, 2021 ; Keller, 2016 ; Kepios, 2021). Cependant, les médias sociaux sont différents des médias traditionnels et exigent que les entreprises s'y adaptent, au risque de rater leur cible (Holt, 2016 ; Marr,2018). Le domaine du sport professionnel peine à s'y adapter. Dans le domaine du marketing et du sport professionnel, l'engagement des consommateurs (CE) sur les réseaux sociaux est l'un des sujets de recherche les plus populaires (Shugan,2021). Choisir du contenu qui engage les consommateurs est essentiel pour rentabiliser son investissement (Holt,2016). Pour identifier ce contenu, nous répondons à la question de recherche suivante : **Comment l'interrelation entre le contenu publié par les entreprises et le choix de la plateforme de médias sociaux peut-elle avoir un impact sur l'engagement des consommateurs ?** Pour ce faire, nous procédons à l'analyse de 5000 publications provenant de 233 organisations et 48 sports différents, obtenues par *web scraping* sur Twitter, Facebook et Instagram. Les données sont codées et analysées à l'aide d'une grille développée par Nepomuceno et al. (2020). Ainsi, nous segmentons le contenu publié par les organisations sportives en trois dimensions de contenu soit :(a) *la dimension de vente* c'est-à-dire les contenus ayant pour objectif de vendre, (b) *la dimension de qualité* c'est-à-dire les contenus qui font la promotion des caractéristiques symboliques ou hédoniques de la marque (Nepomuceno et al.,2020 ; Tafesse et Wien, 2018) ; (c) *la dimension sociale* c'est-à-dire les contenus qui nourrissent la relation entre la marque et ses utilisateurs (Nepomuceno et al.,2020). La dimension de contenu la plus utilisée par les organisations sportives est *la dimension de qualité*. Plus de 88 % de toutes les publications incluent la *qualité*. La *dimension de la qualité* augmente l'engagement sur Twitter et Facebook ; en revanche, elle diminue l'engagement sur Instagram. La *dimension de vente* diminue l'engagement sur tous les réseaux sociaux. Enfin, la *dimension sociale* a un effet négatif ou presque nul sur l'engagement sur tous les réseaux sociaux. Pour tenir compte de l'influence du terrain de recherche, le sport professionnel, nous ajoutons une variable : le risque de *collision corporelle* (*Body Collision*) soit la probabilité d'une forte collision, d'un coup violent entre les concurrents ou entre un concurrent et un objet (Mitchell et al.,1985). En divisant les sports selon la présence ou l'absence de risque de *collision corporelle*, des différences significatives entre les deux groupes se dessinent au niveau des trois dimensions. Entre autres, les sports *de collision* affichent une tolérance nettement plus élevée à *la dimension de vente* tant sur Twitter que sur Facebook. Finalement, le contenu est analysé de nouveau en utilisant les quarante-sept sous-dimensions de la grille d'analyse de Nepomuceno et al. (2020) afin de cerner des actions ponctuelles ayant un effet significatif sur l'engagement ou se détachant des tendances observées au niveau des dimensions de contenu. Sans grande surprise, les sous-dimensions de la *dimension de vente* diminuent presque toujours l'engagement. Pour la *dimension de qualité*, seuls *l'accroche, la joie, les faits marquants, les actualités* et *la galerie* favorisent presque toujours l'engagement, quel que soit le réseau social et le risque de *collision corporelle*. Certains cas où le réseau social modère la relation *contenu-engagement* sont à souligner parce qu'ils portent à la réflexion. Parmi ceux-ci, le cas de Twitter qui est le seul réseau social où *les actualités* ont un impact décroissant sur l'une mesure d'engagement. On peut supposer que les utilisateurs de Twitter, qui utilisent la plateforme pour suivre l'actualité plus que tout autre utilisateur de plateforme sont possiblement plus sensibles à la qualité des nouvelles qui leur sont fournies via les fils de nouvelles et les infolettres (Malhotra, 2012 ; Walker et al., 2021). Il y a aussi le cas de la *galerie* sur Instagram, qui contrairement à la *galerie* sur Twitter et Facebook entraîne une diminution de l'engagement. Nous soupçonnons qu'en raison du grand nombre de photos partagées sur la plateforme, les consommateurs subissent ce que Bai et al. (2020) appellent une surcharge. Finalement, si les résultats au niveau des grandes dimensions de contenu indiquent que la *dimension sociale* a un effet décroissant ou quasi nul sur l'engagement des consommateurs en ligne, ses sous-dimensions cachent plutôt des influences qui s'opposent, variant selon le choix du réseau social et le risque de *collision corporelle* selon le sport suivi. Pour les chercheurs et les spécialistes du marketing, cette étude offre des indications sur les stratégies de publication de contenu les plus susceptibles de stimuler l'engagement sur chaque réseau social et sur celles à éviter.

Mots clés : contenu généré par l'entreprise, engagement, analyse du contenu, médias sociaux, sport professionnel

Summary

Social networks have transformed communications and commerce (Edosomwan et al., 2011). With 58 % of the world's population now using them, a growing share of companies' media budgets is now invested in them (Drenik, 2021 ; Harris Poll, 2021 ; Keller, 2016 ; Kepios, 2021). However, social media is different from traditional media and requires companies to adapt to it, at the risk of missing their target (Holt, 2016 ; Marr,2018). The professional sports field is struggling with this adaptation. In marketing and professional sports, consumer engagement (CE) on social networks is one of the most popular research topics (Shugan,2021). Choosing content that engages consumers is critical to getting a return on investment (Holt,2016). To identify this content, we answer the following research question : **How can the interrelationship between content published by companies and the choice of social media platform impact consumer engagement ?** To do so, we conduct an analysis of 5,000 posts from 233 organizations and 48 different sports, obtained by web scraping on Twitter, Facebook, and Instagram. The data are coded and analyzed using a grid developed by Nepomuceno et al. (2020). Thus, we segment the content published by sports organizations into three content dimensions, namely:(a) the *selling* dimension i.e., all content that has the objective of selling, (b) the *quality* dimension i.e., all content that promotes the symbolic or hedonic characteristics of the brand (Nepomuceno et al.,2020 ; Tafesse and Wien, 2018) ; (c) the *social* dimension i.e., all content that nurtures the relationship between the brand and its users (Nepomuceno et al.,2020). The content dimension most used by sports organizations is *quality*. Over 88 % of all publications include *quality* contents. The *quality* dimension increases engagement on Twitter and Facebook ; in contrast, it decreases engagement on Instagram. The *selling* dimension decreases engagement on all social networks. Finally, the *social* dimension has a negative or near-zero effect on engagement on all social networks. To take into account the impact of our research field, professional sports, we introduce a new variable : the risk of *body collision*, i.e., the probability of a strong collision, a violent blow between competitors or between a competitor and an object (Mitchell et al., 1985). By dividing the sports according to the presence or absence of *body collision* risk, significant differences between the two groups emerge on all three dimensions. Among other things, *collision* sports show a significantly higher tolerance to the *selling* dimension on both Twitter and Facebook. Lastly, the content is further analyzed using the forty-seven subdimensions of the Nepomuceno et al. (2020) analysis grid to identify one-off actions that have a significant effect on engagement or stand out from the trends of the dimensions. To no great surprise, the subdimensions of the *selling* dimension almost always decrease engagement. For the *quality* dimension, only *Hooking*, *Joyful*, *Highlights*, *News*, and *Gallery* almost always drive engagement, regardless of social network and *body collision* risk. There are some cases in which social networks moderate the content-engagement relationship that should be mentioned because they are noteworthy. One of these is the case of Twitter, which is the only social network where *News* has a decreasing impact on one of the engagement measures. Presumably, Twitter users, who use the platform to follow *News* more than any other platform user, are possibly more sensitive to the quality of *News* provided to them via news feeds and newsletters (Malhotra, 2012 ; Walker et al., 2021). Then there is the case of *Gallery* on Instagram, which unlike *Gallery* on Twitter and Facebook leads to a decrease in engagement. We suspect that due to the large number of photos shared on the platform, consumers experience what Bai et al. (2020) call overload. Ultimately, while the results at the broad content dimension level indicated that the *social* dimension had a decreasing or near-zero effect on consumers' online engagement, its subdimensions instead hide opposing influences, differing by choice of social network and risk of *body collision* according to sport followed. For both researchers and marketers, this study offers insights into which content publishing strategies are most likely to boost engagement on each social network and which to avoid.

Key words : firm generated content, engagement, content analysis,
social media, professional sports

Abstract

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Abstract :

This study explored how content generated by professional sports firms influences consumer engagement on Twitter, Facebook, and Instagram. Four research questions guided this investigation, focusing on the following : proportions in which sports companies post various types of contents, the reactions they elicit across social networking sites and different types of sports, and the specific actions that significantly influence engagement on social networking sites. The encoding grid of Nepomuceno et al. (2020), where content is divided into four dimensions : [1] *Structural*, [2] *Selling,* [3] *Quality*, and [4] *Social,* was used to perform the content analysis of the 5,000 posts. The inferential statistics showed that there were significant variations across Twitter, Facebook, and Instagram as well as between sports depending on whether there was a risk of *Body Collision i.e.,* the probability of a hard impact between competitors or between a competitor and an object (Mitchell, 1985). This study has implications for Content Managers across all areas that have communities across Twitter, Facebook, and/or Instagram, particularly for those in the Sports field.

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Abbreviations

B	Billion
CE	Consumer Engagement
ESPN	Entertainment and Sports Programming Network
eWOM	Electronic Word-of-Mouth (eWOM)
FB	Facebook
FGC	Firm Generated Content
IG	Instagram
K	Thousand
LOG	Decimal Logarithm or log10
MLS	Major League Soccer
MM	Million
OSMC	Owned Social Media Content
SMS	Short Message Service
SNS	Social Network Sites
TW	Twitter
twttr	Twitter's original Name (with the vowels removed)
UGC	User-Generated Content
UEFA	Union of European Football
WWE	World Wrestling Entertainment

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Chapter 1 - Background of the study

Consumer engagement (**CE**) is one of the most popular topics among marketing researchers (Shugan, 2021). Given that nearly 58 % of the world's population uses social media, (Kepios, 2021), researchers are swimming in data, the source of valuable knowledge (Huphreys and al.,2018). Social media has transformed the way people communicate and conduct business (Edosomwan et al., 2011). Business investment in social media is steadily increasing (Harris Poll, 2021), so much so that it will soon replace mass media (Keller, 2016). However, social media, with no apparent hierarchy, is very different from traditional media, and brands that don't adapt their communications are falling by the wayside (Holt, 2016).

In the beginning, brands hoped that social media would function as a sort of " red phone "- a direct line of communication with users on the other end of the line, coming from all over the world, just waiting for their messages to be broadcast (Weiss, 2013). While social media has delivered on its promise of attracting large numbers of users worldwide, with audiences increasing 741 % between 2000 and 2014 (Liébana et al., 2017), these user numbers have not converted into sales. Partly because unlike mass media before the advent of DVRs, social media users have the power to cherry-pick advertising content as they see fit (Holt, 2016). On Twitter, a brand's tweet is only seen by an average 1 % of its followers (Sullivan, 2014). Also, the other characteristic that works against advertisers is that social media is flooded with content. Three years ago, Forbes shared some stunning data : *over the last two years alone, 90 percent of the data in the world was generated* (Marr, 2018). Data is growing exponentially. Every minute, Instagram users share 65K of photos, Facebook users share 240K of photos, and Twitter users post 575K tweets (Business Wire, 2021). Advertisers must produce content that stands out in this glut in order to be chosen by users and shared, because consumer-to-consumer sharing is increasingly crucial for effective marketing (Harris Poll, 2021). The virality or reach of content published by brands increases when users share it across their network (Villarroel et al., 2019). In general, a publication is said to go viral when it reaches an unusually large audience (Han et al., 2020).

The study of CE is useful for understanding how marketing affects sales and profitability. Some authors have studied the very beginning of the process, i.e., the motivations and gratifications for using social networks and one platform over another (Alhabash and al., 2017 ; Phua and al., 2017 ; Chi, 2011 ; Baldus et al., 2015.) Others have instead sought to understand the mechanics of CE on Social Networking Sites (**SNS**) (Jahn and Kunz, 2014 ; Jiang et al., 2016 ; Noguti, 2016 ; Pletikosa Cvijikj and al., 2013 ; Ashley and Tuten, 2015). Finally, some have focused instead on the impact of social networks on the economic performance of businesses, measured in sales intent or turnover, both online and offline (Beukeboom et al., 2015 ; Goh et al., 2013 ; Colicev et al., 2017 ; Bai and Yan, 2020 ; Song et al., 2019 ; Yang et al., 2019 ; Kumar and al., 2016 ; Baker et al., 2015). However, there is very little empirical research on the type of content that impacts engagement, valuable information for marketing practitioners.

1.1 Statement of the problem

As an ever-increasing share of a company's media budget is invested on social networks, choosing which content to generate to feed them is critical to getting more bang for your buck (Holt, 2016). To make the right choice, many questions remain unanswered : what type of content engages consumers and what type repels them ? On social networks, is it better to only publish content with a social dimension ? Does sales content repel users ? Given the way they work, do images engage users more on Instagram than on Twitter ? Does the type of content that generates the most engagement vary from one social network to another ? From one organization to another ? This thesis seeks to answer these questions. We consider the interrelationship between the content published by companies, the choice of social media platform and its impact on CE.

The question we attempt to answer is the following : **How can the interrelationship between content published by companies and the choice of social media platform impact consumer engagement ?**

1.2 Purpose of the Study

We have three distinct objectives. Our first objective is to measure the impacts of three different content dimensions : (1) the *selling* dimension, (2) the *quality* dimension and (3) the *social* dimension on consumer engagement (measured in numbers of likes and comments) and compare them across social networks, i.e., Twitter, Facebook and Instagram. These content dimensions of the FGC come from Nepomuceno et al. (2020). Next, we determine the extent to which sports organizations and teams respond differently to these types of content. To do this, we test a moderator variable that divides sports into two categories based on the presence or absence of collision risk. Our third goal is to analyze the content, again by subdividing it into smaller categories to find point actions that have a significant effect on engagement. To this end, we use the subdimensions of the Nepomuceno et al. (2020) analysis grid.

1.3 Significance of the study

Our contribution is threefold. Our first contribution is to measure the influence of different types of content (*selling*, *quality*, *social*) published by companies on their official social networks on users' online engagement (measured in likes and comments).

Our second contribution is to measure the moderating effect that the choice of social platform has on the relationship between content and consumer engagement. When we cross-reference our data, we isolate one platform at a time (Twitter, Facebook or Instagram) to determine the extent to which each reacts to each type of content individually. This input is critical, since users are motivated by different rewards depending on the platform they choose (Phua et al., 2017 ; Rubin, 2002). Thus, the match, the *fit* between the content and the user, is not the same from one platform to another. The better the fit, the higher the level of engagement (Zhang et al., 2017), the more consumers will in turn want to share the content in their own community, thus increasing the virality of the publications (Malthouse et al., 2013).

Finally, the choice of the sports industry as an empirical field is ideal in terms of its contribution to the knowledge of user preferences on social networks. The sports industry is expected to reach a value of $183.45 billion by 2025 (Business Research, 2021). The CE of professional sports organizations, offered mainly for spectatorship, is among the highest of any economic field. The industry is global, with markets spanning North America (at 35 %), South America, Asia-Pacific (at 31 %), Europe (Western and Eastern), the Middle East and Africa (Business Research, 2021). These organizations publish an enormous amount of content, two to eight times more than the general industry average depending on the social media (Feehan, 2021).

Champions of popularity on Instagram, among the 15 most followed accounts are four professional sportsmen, Portuguese Cristiano Ronaldo, Argentine Lionel Messi, Brazilian Neymar, Indian Virak Kohli and the American sports brand Nike. On Twitter, two Spanish soccer clubs, Real Madrid Fc and FC Barcelona, a U.S. sports channel, ESPN, and an annual European soccer competition, UEFA, also appear in the top 50 (Social Tracker, 2021 ; Wikipedia, 2021). Sport is a topic of interest, because it is not limited to individuals, but encompasses teams, organizations, leagues, brands. It represents cities, nations, and countries. Sport rises in popularity rankings by overcoming barriers of language and skin color. Following sports is among the world's favorite hobbies, particularly for men who make up 76 % of worldwide sports viewers. According to U.S. figures, the 35-44 age group is the largest (35 %), followed by the 18-34 age group (33 %) and the 45+ age group (23 %) (Lange, 2020 ; Goug, 2022).

The main objective of this research is to determine the type of content that drives the highest level of engagement by platform.

Our paper offers managerial recommendations on how to drive engagement on three different social media platforms. In addition, we confirm the effectiveness of the typology proposed by Nepomuceno and al. (2020) for practitioners and academics to structure unstructured data and derive sport-specific insights (Balducci and Marinova, 2018 ; Briggs and Hodgetts, 2017).

1.4 Definition of terms

Certain terms are central and used throughout the thesis. These are the variables of our research question, as well as those of the theories and models that form the basis of our study and hypotheses. Since the sources consulted sometimes diverge and to avoid confusion, they are defined below. Our definitions are specific enough for another researcher to replicate our study.

1.4.1 Body Collision

Violence and intense rivalry in sports increase spectators' interest and enjoyment (Bryant and Zillmann, 1983). However, for a researcher, drawing the line between a violent and a non-violent sport is a highly subjective act. Mitchell et al. suggest an alternative classification of sports based on the risk of *body collision*, which they define as the probability of a hard impact between competitors or between a competitor and an object (1985) (see Appendix C for a classification of sports by Mitchell). Although Mitchell's article was first published almost forty years ago, it remains a reference and is a precursor to many more (Rice, 2008) (see Appendix D for a classification by Rice). The 48 spectator sports of our sample are categorized using this method (see Appendix E for the classification of our sample based on Mitchell). In this paper, the terms *body collision* and *collision* sports are used interchangeably. Our model also includes other ways of classifying these disciplines, kept as control variables. Hereafter are their operational definitions :

1.4.2 Gender

Spectators of women's sports differ from those of men's sports (Ridinger and Funk,2006).

1.4.3 Team or individual sports

Individual and team sports fans have different motivational profiles. Diversion from the rest of their lives, is the only common motive for both groups (Sloan, 1989 ; Smith, 1988).

1.4.4 Proximity

Geographical ***proximity*** of fan communities : Fans identify with the sports teams in the geographical communities that surround them (Wann and Branscombe, 1990), and this alliance leads to strong and positive feelings (Kolbe and James, 2000).

1.4.5 Content Dimensions

We use content analysis guidelines from a study by Nepomuceno and al. (2020) to divide FGC into four dimensions namely : (1) the *structural* (or *architectural*) dimension which consists of the basic attributes of the post, e.g., brand, country of origin, platform from which the content is taken, media type (image, video, text, GIF) and engagement metrics (likes, comments, shares, etc.) ; (2) the *selling* dimension, which consists of content whose objective is selling, whether implicit or explicit (with a hyperlink that leads to a sale), e.g., pushing the sale of products via a call to action, a publication that promotes an event, through sweepstakes or cross-promotions ; (3) the *quality* dimension, which consists of any content that celebrates the brand or its products via eye-catching, immersive images, close-ups or concept art. (Erdem and Swait, 1998) ; (4) the *social* dimension which consists of all actions that nurture the relationship between the brand and its users, e.g., intimate, behind-the-scenes, evangelistic content where messages invite fans to contribute to the development or promotion of the product. The data were coded in a binary way, with no grey area, either there is absence or presence of the dimension.

1.4.6 Consumer engagement (CE)

The use of the term *engagement* in this essay is a deliberate simplification to facilitate reading of the text. Rather, it should be referred to as actions that measure engagement. Engagement is a psychological state that reflects interactive experiences and user co-creation with a company and highlights the active role of the consumer (Brodie and al., 2011 ; Verleye and al., 2014). According to Van Doorn and al (2010) : "Consumer engagement is a customer's behavioral manifestation toward a brand or firm, beyond purchase, resulting from motivational drivers such as eWOM, recommendations, helping other customers, blogging, writing reviews." Malthouse and al. distinguish between two levels of CE : low engagement, where the user consumes content passively or with basic feedback such as a like on Facebook, and high engagement, where the user is actively involved in co-creation (2013). Within our study, we consider all levels as engagement, without distinction. In this text, the terms consumer engagement, customer engagement and user engagement are used interchangeably.

1.4.7 Firm Generated Content (FGC)

FGC is a marketing communication initiated by the company on its official SNS to interact with customers (Kumar and al., 2016). It is also found in the literature under the name of marketer-generated content (**MGC**), company-generated content (**CGC**) and owned social media content (**OSMC**) (Nepomuceno and al. ; Timoshenko and al., 2019). The content published on SNS by companies can be segmented according to several variables. Hereafter are the operational definitions of those kept as control variables:

1.4.8 Scheduling

The holidays are either religious or national celebrations when most workers have time off work and therefore more time for social media use, which can impact CE. The literature suggests that the holiday season spans from Thanksgiving to New Year's Day (Swilley & Goldsmith, 2013). We add Valentine's Day to this categorization since the publication of associated contests and contents by brands during the month leading up to it increases CE (Plato, 2015).

1.4.9 Vividness

Vividness is related to the number of sensory dimensions, cues and meanings presented (colors, graphics, sound, animation, bandwidth). It is also referred to as media richness theory (Fortin and Dholakia, 2005). Previous studies have shown that higher vividness leads to higher levels of CE (Pletikosa Cvijikj and al., 2013). In our model, it is a control variable.

1.4.10 Social Media

There is some confusion between social media, social media platforms, networks and whether they differ from the concepts of Web 2.0 and UGC (Kaplan and al., 2010).

Social media are a group of Internet applications that build on the foundations of Web 2.0 and allow the creation and exchange of UGC. While there are several types of social media, Twitter, Facebook, and Instagram are all content communities, as well as social networking sites (**SNS**) that allow communications via text, the sharing of photos, videos, and other forms of media (Kaplan et al., 2010). In this thesis, we use the terms social platforms, social media, and SNS interchangeably.

1.4.11 Web 2.0

Web 2.0 is the platform where content and applications are no longer created and published by individuals in a one-way fashion but are continuously modified by all users in a participatory and collaborative way (Kaplan and al., 2010).

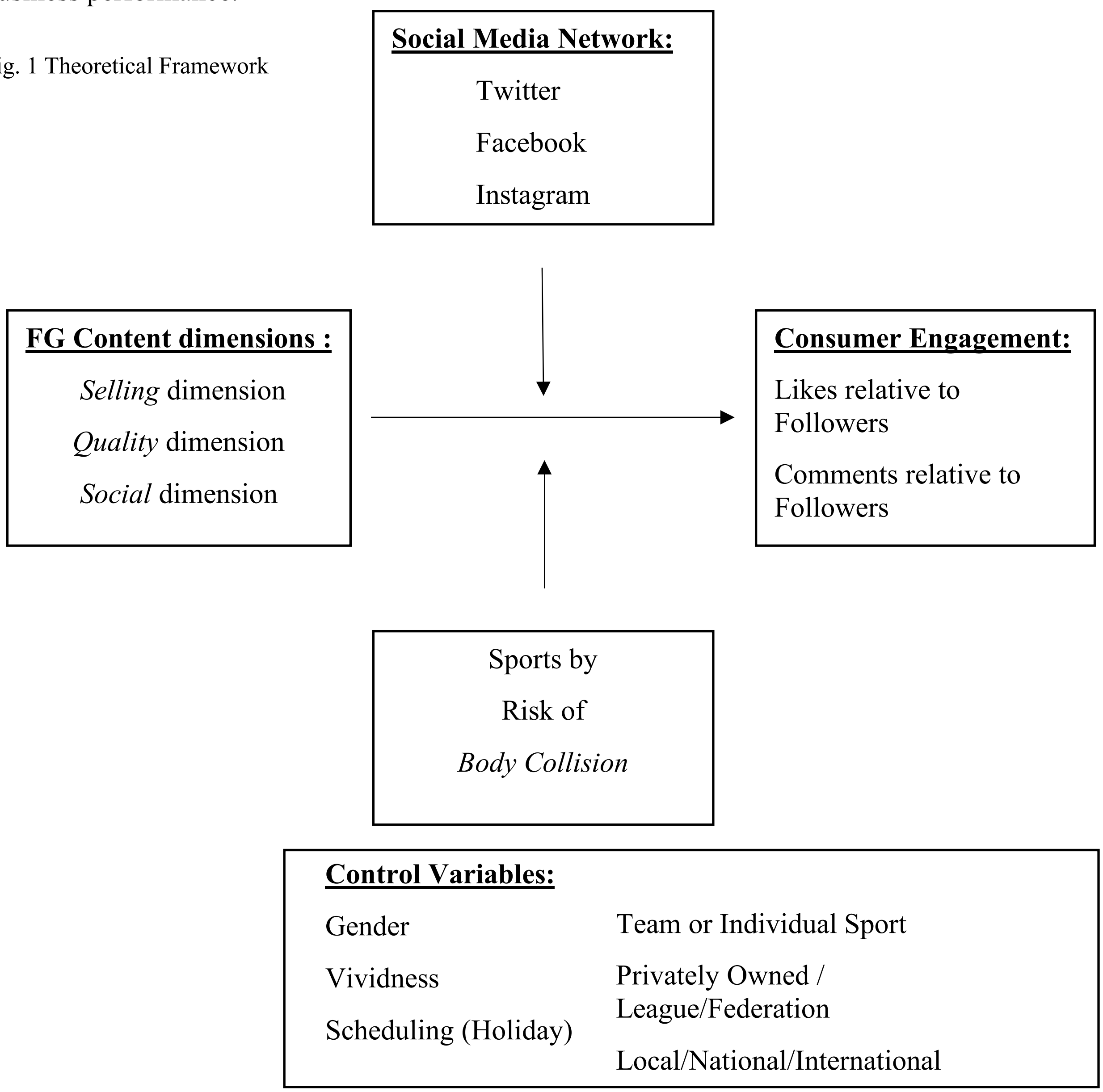
1.4.12 User-generated content (UGC)

If Web 2.0 is the ideological and technological foundation, UGC is the sum of all the ways people use social media. UCG describes the various forms of content publicly available and created by users (Kaplan and al., 2010).

1.5 Theoretical Framework

Based on the theory, we believe that relationships exist between variables in the FGC and that these systematically explain regularities in user behavior on social networks. These relationships are illustrated by the framework below. This framework illustrates our research questions, serving as a starting point for our research methodology. Our model is a variation of Nepomuceno and al. (2020). Although they have many similarities, Nepomuceno and al. (2020) do not focus on online user engagement, rather their output variable is business performance. In their model, community size is used as a moderating variable. When choosing the sites from which the data will be extracted, we set a minimum number of followers, so that the communities have a homogeneity of size. However, the size of the communities is not part of the variables analyzed in the subsequent phases. Although our model is similar, our moderating variable is rather *body collision*. Our theoretical model is a variation of theirs in that it uses the same content dimensions of the FGC as dependent, or predictor, variables, removing only one, the structural dimension. The others, the *selling* dimension, the *social* dimension, and the *quality* dimension, are the same. Our model, largely inspired by theirs, explores the ways in which interactions between the content dimensions impact engagement rather than business performance.

Fig. 1 Theoretical Framework



1.6 Research Questions

The following are research questions guiding this study of CE on the official SNS of over 200 sports organizations.

1. What dimension of content do sports companies predominantly use on their official social networks ?
2. To what extent are the different dimensions of content generated by sports organizations associated with consumers' engagement on their official social networking sites ?
3. How does the risk of *body collision* in sport impact the relationship between the content dimensions of the FGC and the CE ?
4. To what extent are the different subdimensions of content generated by sports organizations associated with consumers' engagement on their official SNS ? How does the risk *of body collision* in sport impact the relationship between the content subdimensions of the FGC and the CE ?

1.7 Limitations

The study has the following limitations:

1. More than 71 % of the data is sourced from American organizations or teams ; consequently, our results may not be generalizable to all continents.

2. Time and manpower to analyze the data were limited. Without limitations, we could have added sentiment analysis, using LWC or Vader, (Hutto and Gilbert, 2014) or voice analysis based on pitch, speech rate, and intensity (Balducci and Marinova, 2018). Publication times and dates could also have been added to the regressions or control variables, given the existing literature (Pletikosa Cvijikj and al., 2021). Our methodology, guided by our resource limitation, impacts the interpretation of the results.

3. During the initial data extraction, only one third of the engagement data is taken. Once the data is coded, the posts are manually reopened one by one, and the

engagement metrics added to the Excel document. More than three months have passed. Some teams have removed their posts. When all engagement metrics are considered, i.e. the number of followers, views, comments, likes and shares, 24 % of the data is still missing. To measure engagement, we will therefore only use the number of followers, likes and comments for which an average of only 1.56 % of the data is missing.

4. Stories are instant and ephemeral. Since the study took place over several months, stories could not be extracted or stored on Instagram. As one of the social network's most popular features, especially among younger users (Statistica, 2021), their omission may play into the interpretation of the results.

1.8 Delimitations

The delineations used by the researcher in this study were determined by the desire to understand the relationship that exists between the FGC and CE. Only organizations and teams that communicate in English were selected. The study focuses on three social media : Twitter, Facebook, and Instagram, which have different audiences and functionalities, resulting in a large picture (Statistica, 2021). We set the minimum number of followers at 70,000 to have consistency in size. A higher number would exclude most female or mixed-gender teams or athletes that represent 22 % of the sample. The study covers teams, organizations, leagues, sports groups, but excludes personal pages in the name of a single athlete.

1.9 Organization of the study

This research study is presented in five chapters. Chapter 1 includes the background of the study, statement of the problem, purpose of the study, significance of the study, definition of terms, theoretical framework, research questions, limitations, and delimitations of the study. Chapter 2 presents a review of the literature, which includes a concise overview of the creation of social networking sites and their actual audiences, the content that firms are generating, consumers' engagement, and some research on content dimensions. Chapter 3 describes the methodology used in this study. Chapter 4 presents the study's findings. Chapter 5 provides a review of the main results, a discussion of the study's main findings, implications of the findings both from a theoretical and practical standpoint, recommendations for further research, and conclusion (Lunenberg and Irby, 2008).

Chapter 2- Literature review

This chapter presents the rationale for our research on the relationship between firm generated content and consumer engagement. Researchers in marketing have been investigating consumer engagement on social networking sites for approximately 20 years. Yet, over the past 20 years, the landscape has changed significantly. Nowadays, user preferences vary from one platform to another, numbering in the hundreds. So, we begin with a brief overview of the evolution of social networks to this day and the relevance of having chosen Facebook, Twitter and Instagram as our research fields.

As consumers increasingly turn to social media, particularly with the pandemic, it is critical that we understand the drivers of engagement in brand communities. Firm generated content analysis is the source of much marketing research. Although there is no consensus on how to categorize firm generated content, the body of research done over time has many similarities. Our study seeks to build on these.

As such, this study seeks to examine the moderating effect of three different social networking sites on the relationship between content dimensions and consumer engagement, considering a professional sports context. The following literature review is organized into four sections : (a) Brief history of social networks, and Facebook, Twitter and Instagram today, (b) Firm Generated Content (FGC), (c) Consumer Engagement (d) Content Dimensions.

2.1 Brief history of social networks, and Facebook, Twitter and Instagram today

The first SNS operated on the principle of degrees of separation, with communities connecting people who were related in some way. In 2002, Friendster was the first to achieve great success with 115 million subscribers. LinkedIn, Myspace and Facebook followed on the same principle soon after.

Since then, the social landscape has evolved. 57.6 % of the world's inhabitants have an account on a social network, a statistic that hides important disparities. While more than 90 % of North Americans have an account on a social network, this figure is as low as 24 % in some parts of Africa and 68 % in East Asia, which together account for nearly a quarter of all users of social networks (Agence France-Presse, 2021).

For these networks, there are still growth prospects of billions of new users in developing countries. Currently, India is the fastest growing country, with 130 million new users joining platforms. For advertisers however, the return on investment is lower, given that users in developing countries have less discretionary income than early adopters. According to Facebook, the average revenue per user would be $41.41 for a person signing up in the U.S., while in the Asia-Pacific region, the figure is $3.57 (Dean, 2021).

As the list of social media platforms on the internet is always increasing, our study focuses on three popular media, namely Facebook, Twitter, and Instagram, which differ in terms of functionalities and audiences. Their number of users continues to grow, thanks to the conquest of new markets ; the curtain on back-channel practices has however been drawn.

2.1.1 Facebook

In 2004, Mark Zuckerberg and some of his colleagues launched the first version of Facebook. The SNS was initially limited to students at Harvard University. By 2006, it opened to all users over the age of 13. By 2011, it had reached a popularity of 800 million active users (Arora and Saani, 2019).

Since 2017, Facebook, now known as Meta (Rodriguez, 2021), has been the subject of several controversies related to the control of information (Branco, 2021), tax evasion (BBC, 2020), lack of privacy (Leetaru, 2019), use and deletion of data for commercial purposes (Singer, 2018). Despite this, Facebook remains the world's most popular social media with 2.910 billion monthly active users, or about 36.9 % of the world's population. Every day, 1.93 billion people use Facebook and Facebook is still growing. In the last 12 months alone, the platform acquired 170 million additional subscribers (Kepios, 2021).

In terms of market penetration, the largest number of active users is found in North America (194 million), followed by Indonesia (143 million), Brazil (127 million), Mexico (96 million), The Philippines (91 million), Vietnam (74 million), Thailand (55 million), Bangladesh (48 million) and Egypt (48 million) (Kepios,2021).

Worldwide, men are more likely than women to have access to the internet. They are overrepresented on Facebook, accounting for 56.5 % of total users. The median age of the Facebook audience is 31 (Kepios, 2021). Contrary to popular belief, the data shows that young people are still among the largest users of Facebook worldwide. The audience breaks down as follows : 13 to 17 years old (5.6 %), 18 to 24 years old (22.8 %), 25 to 34 years old (31.1 %), 35 to 44 years old (17.8 %), 45 to 54 years old (10.8 %), 55 to 64 years old (6.7 %), 65 years old and up (5.2 %) of the total audience.

Facebook is the preferred network for 19.7 % of users to follow brands (Phua et al., 2017). They are highly engaged, with 70 % logging into the platform at least once a day (Duggan, 2015). Originally described as a friend networking site, the main reason given by users for using the platform was originally keeping in touch with friends, family and locating old friends. (Alhabash et al., 2017 ; Quan-Haase et al., 2010 ; Raacke et al., 2008). Since then, the reasons for using the platform have evolved. Users now mention the need for entertainment, self-documentation, and media appeal (Alhabash et al., 2014 ; Alhabash et al., 2012 ; Karlis, 2013). Indeed, in 2021, nearly one-third of U.S. adults (31 %) reported getting their news regularly on Facebook. These regular news consumers are 60 % white and 64 % female (Walker et al., 2021).

2.1.2 Twitter

In 2006, Jack Dorsey invented *twttr*, an SMS communication platform where groups of friends could find out what others were doing based on their status updates (MacArthur, 2020). Users were then limited to 140 characters, to comply with cell phone carrier limitations. In 2017, Twitter adapted to the rise of smartphones and moved to a 280-character limit. Microblogs are generally as short as a newspaper title and subtitle. They are instantaneous, but not invasive, because users can consult them asynchronously. They are thus archived, indexed on search engines, and adaptive (Jansen et al., 2009).

Despite a major hacking scandal in 2020, in which several individual and corporate accounts were compromised, Twitter maintains its growth (Thompson, 2020). The platform shows an increase of 24 million users (or 12.8 %), between October 2020 and October 2021. So much so that today, about 7.1 % of all people aged 13 and over in the world use Twitter, a percentage that rises to 8.9 % if we ignore the population of China, where Twitter is blocked (Kepios, 2021).

Men are vastly overrepresented on the platform, as they represent 70.4 % of global users. Users between the ages of 18 and 24 make up the largest share of the audience. The audience by age group breaks down as follows : 13-17 (5.1 %), 18-24 (27.9 %), 25-34 (24.3 %), 35-49 (23.0 %) and 50+ (19.7 %).

In terms of market penetration, the largest number of active users is found in North America. Again according to Kepios (2021), the breakdown by country of the top users is as follows : the United States of America (77.8 million), Japan (58.2 million), India (24.5 million), Brazil (19.1 million), the United Kingdom (19.1 million), Indonesia (17.6 million), Turkey (16.3 million), Saudi Arabia (14.2 million), Mexico (14.0 million), and Thailand (11.3 million). Twitter users significantly over represent populous countries and regions, suggesting that entire regions may be significantly underrepresented (Mislove and al., 2011).

People use Twitter for information, research, questions and to share information and opinions about brands and products (Jansen and al., 2009). 19 % of all tweets mention the name of a product, brand, or an organization (Jansen and al., 2009). Twitter is the preferred network for 9.2 % of users to follow brands (Phua and al., 2017).

Twitters users strongly identify with their brand community and have a strong desire to adhere to it (Phua and al., 2017). Users who visit the same brand communities frequently share common brand-related goals and consider themselves as part of a larger community (Algesheimer and al., 2005, Carlson and al., 2008, Muñiz and Schau, 2007). The real-time updates, retweet feature, and dissemination of messages in their communities via hashtags encourage member participation (Jin and Phua, 2014). Electronic Word-of-Mouth (**eWOM**) empowers regular consumers to influence brand image and perceptions (Reynolds, 2007). Opinions expressed on Twitter are polarized, 52 % being extremely positive and 33 % extremely negative. Customers with more moderate experiences or opinions very seldom share their experiences (Anderson, 1998 ; Dean, 2021). The exchanges in brand communities have an influence on the image of a brand, on its notoriety (Esch and al., 2006). This influence, whether negative or positive, will influence consumers' satisfaction, trust, and attachment to the brand. Ultimately, it will have an impact on the brand's business performance (Park and Lee, 2009).

Twitter is also a regular source of news for 13 % of all American adults. It stands to reason that Twitter is heavily used as a news source among its users. Indeed, again referring to users in the United States, while Twitter is used by about 23 % of American adults, more than half of them or 55 % use it regularly as a news source (Walker and al., 2021).

2.1.3 Instagram

Instagram is a photo and video-sharing social media application that was launched in 2010. A Meta property since 2012 (Reiff, 2021), it allows users to take photos, apply filters to them, and share them on the platform itself, as well as on other platforms like Facebook and Twitter (Stec, 2020). Since its launch, Instagram has added a messaging feature and another of ephemeral stories, modeled after Snapchat, which disappear after 24 hours, one of its most popular features (Blystone, 2020 ; Statistica, 2021).

Instagram has approximately one billion monthly active users. It is particularly popular in India and the United States, with 180 million and 170 million users respectively. According to figures compiled in the United States, Instagram is used by more women than men (44 % vs. 36 %) (Pew Research Center, 2021). Its user base is young, with less than a third of its users over the age of 34 (Statistica, 2021).

Instagram is often used as a style guide (Phua and al., 2017) and to pass the time (Lenhart and al., 2015). Brand followers on Instagram have a higher level of engagement in the brand community, than on any other platform. They are more likely to participate in brand activities, follow community rules, and remain loyal for a long period of time (Hollebeek and al., 2014). This engagement with the brand community may contribute to users' future intention to purchase the brand's products (Jin and Phua, 2014 ; Muñiz and Schau, 2007).

These users stand out for their sociability : they befriend the opposite sex, enjoy meeting new people, and are less inhibited towards strangers (Phua and al., 2017). They like to thank people, let others know they care, offer help, encourage, and show interest (Quan-Haase and Young, 2010).

Like many other social networks, Instagram is a regular source of information for 11 % of Americans. However, the demographic differences between Instagram users are less clear-cut than with Facebook users. Approximately 36 % of regular news consumers are White adults, 20 % are Black adults, and 33 % are Hispanic adults (Walker and al., 2021).

Instagram also had its share of controversy. Several researchers link Instagram use to high levels of anxiety, depression, bullying, and FOMO, “fear of missing out”, among teens and young adults (MacMillan, 2017), facts ignored by the company to preempt monetary benefits (Subin, 2021).

2.2 Firm generated content (FGC)

Despite the scandals experienced by these three giants, social networks continue to attract half a billion new users each year (Agence France-Presse, 2021). Unsurprisingly, Covid amplified the popularity of social networks. While many countries sounded the alarm and confined their citizens to their homes, people turned to social networks to connect with friends and family (62 %) and for entertainment purposes (48 %). It was the only channel that remained open during this time (Drenik, 2021). Thus, the annual global market for advertising on social networks is growing rapidly, representing 97.7 billion dollars (Agence France-Presse, 2021). This increase in investment is accompanied by an increase in FGC. This represents a wealth of information, albeit in a raw state, which must then be structured, manually or automatically, before it can be quantitatively analyzed to think about deriving insights. As a result, more than 80 % of enterprise data is unstructured, a figure that is increasing (Balducci and Marinova, 2018 ; Berger and al., 2019). Enterprise-generated content is so abundant and opaque that marketers talk about *demystifying* it and refer to it as *dark analytics* (Briggs and Hodgetts, 2017). FGC is crucial as it has the potential to shed light on consumer behavior. It has a positive and significant effect on customer spending and cross-purchasing behavior, i.e., the purchase of additional products and/or services from the same company (Santiago and al.,2022 ; Valentin Ngobo, 2004). Brand-generated content is an essential part of a media mix. It works synergistically with different media such as television and e-mail, but also with offline purchases. Customers increase their spending when information about a brand and product is abundant and accessible. This builds their trust and increases customer spending (Yang and al., 2019).

2.3 Consumer engagement

If this increase in information leads to more purchases, it's because users are engaged. Engaging on one of a brand's official platforms, a brand community, is often motivated by an initial need for information. Engaged consumers talk about their own experiences with the brand's products/services and influence other members, thereby championing the brand. These consumers are more loyal, emotionally attached, and have greater trust in the brand (Brodie and al., 2013). The engagement of these consumers online leads to a significant increase in consumer purchases (Goh and al., 2013 ; Malthouse and al., 2016). Thus, CE can predict purchase behaviors and brand loyalty (Hollebeek and al., 2014 ; Pham and Avnet, 2009 ; Avnet and Higgins, 2006 ; Schau and al., 2009). It is a performance metric measured in the number of actions taken by consumers in response to content posted by brands on social media (commenting, liking, retweeting, or sharing)

(Barger and al., 2016). The more public the interaction, the more viral the effect on the social network (Aldous and al., 2019).

2.4 Content dimensions

However, while the right mix of FGC can have a positive impact on engagement and business performance, publishing too much content instead leads to overload (Bai and al., 2020). Nepomuceno and al (2020) observe a similar phenomenon, which however is not due to the amount of content disseminated by the organizations, but to the content itself. Rather than talking about overload, they talk about fatigue (Nepomuceno and al, 2020). Across the literature, there is no consensus on how to divide the content published by firms to measure its influence on CE on each SNS. Previous research divides content far less comprehensively than the Nepomuceno and al. (2020) typology used here and is often limited to a single social media platform (Gavilanes and al., 2018, Kim and al., 2015 ; Lee and al., 2018 ; Shahbaznezhad and al., 2021). Below, are several different comparative studies that will prove helpful in analyzing my data.

2.4.1 Selling dimension

Concepts very close to the *selling* dimension (Nepomuceno and al., 2020) are studied by other authors, under different names, including transactional content (Shahbaznezhad and al., 2021), task-oriented contents (Kim and al., 2015), remunerative content (Dolan and al., 2019) or content encouraging immediate sales (Swani and al., 2013). However, not only do these types of content promote sales (Han and al., 2020), but they focus on the use of direct calls to purchase and explicit marketing (Swani and al., 2013). Nepomuceno and al.'s (2020) dimension is broader as it also includes *Implicit Selling*, *Prize Draws* and *Event Promotions*. Research shows that engagement is not affected in the same way by the sales dimension from one SNS to another.

2.4.1.1 Selling on Facebook

On Facebook, direct calls to purchase decrease consumer engagement and undermine trust and brand image (Swani, 2013). However, while direct selling messages on their own deter engagement, when paired with brand personality (human characteristics), engagement increases (Lee and al., 2018). Consumers value their favorite brands' humanity, humor, emotions, wit, and charitable actions (Aaker, 1997 ; Weiss and Huber, 2000 ; Lee and al., 2018).

This not only works well to increase engagement but it also boosts brand loyalty (Swani and al., 2013). In contrast to *Explicit Selling*, *Implicit Selling*, not seeking to make an immediate sale, such as *Event Promotions*, *Prize Draws*, and entertaining content, is most likely to have an eWOM effect (Coelho and al., 2016). Facebook is a strong eWOM multiplier, where every like is relayed to an average of more than about 130 peers, who may in turn re-post this content back into their own communities (Swani and al., 2013).

2.4.1.2 Selling on Twitter

On Twitter, not only do direct calls to purchase decrease following, they decrease retweets by about 32 %. While over half of Twitter members rely on Twitter as their news source (Walker and al., 2021), when they subscribe to a brand's news feed, they grant the brand a license to send them updates and information about the company. By blatantly promoting its products, the brand is violating this implicit agreement. These users then claim to be turned off by the brand (Malhotra, 2012).

2.4.1.3 Selling on Instagram

Like those on Facebook and Twitter, users on Instagram favor *Implicit Selling* over *Explicit Selling*. If Instagram followers have a positive response toward announcements about special events, contests, and giveaways, it is because they are pleasure-seeking Hedonists. Such posts are shared more broadly in followers' circles of friends, because they maintain a value beyond their community (Coelho and al., 2016).

2.4.1.4 Selling in short

Nevertheless, companies publish a huge amount of sales content, ranging from a third to half of all FGC (Kim and al., 2015). According to Ding and al. (2014), while such content may not directly boost engagement, people take it as their own, and circulate it in their own communities, thereby increasing both the brand community and the firm's performance. However, for sales-oriented content to flow, these communities must be in an active state, a condition which brands reach by maintaining connections to members and generating socially oriented content, two interrelated dimensions (Ding and al., 2014).

2.4.2 Social Dimension

The focus of *social* dimension is socialization, and its aim is to establish and sustain consumer-brand connections (Ding and al., 2014 ; Kim and al., 2015). These connections can be in the form of small talk, storytelling, as well as insider discussions (Ding and al., 2014). It may also be a prompt to reply to a question, to vote, to fill in blanks, to like, to comment, or to share a post (Kim and al., 2015). Throughout the literature, numerous researchers hold similarly constructs, although specifics as well as the names differ, such as social content dimension (Nepomuceno and al., 2020), interaction-oriented content (Kim and al., 2015), interactional or socially interactive content (Shahbaznezhad and al., 2021). Still, while many researchers have investigated how social content affects consumers' engagement, there is no consensus as to their findings (Shahbaznezhad and al., 2021). The results differ across economic fields, moderator variables, researchers and SNS.

2.4.2.1 Social on Facebook

On Facebook, Pletikosa Cvijikj and al. (2013) found evidence that Entertaining content - i.e. posts without reference to a brand or product and those which explicitly request consumers' participation (also known as *Crowdsourcing*) - increase users' engagement, with respect to both likes and comments. Depending upon the source though, the findings vary. According to Dolan and al.(2019), social (or relational) based content increased likes but showed no effect on comments. In contrast, based on Luarn and al. (2015), across all the posts, they would exhibit the highest comments' activity, yet extremely low likes and sharing levels. For Coelho and al. (2016) however, there would not be a significant relationship between the social content and the engagement on Facebook. There exists a consensus that the value of social content is lost beyond the Facebook brand community.

2.4.2.2 Social on Twitter

On Twitter, contrary to Facebook, *Crowdsourcing*, that is, inviting the crowds, the followers of a brand's community to engage, to interact through a vote or a response to a question, reduces the sharing of an average post by 30 % (Malhotra, 2012).

2.4.2.3 Social on Instagram

On Instagram, while its impact on commercial performance is rather limited (Nepomuceno and al, 2020), social content has a significant positive effect on the growth of brand communities, i.e., increasing the number of followers, a key factor in making a return on investment in such communities (Ding and al, 2014). If the MLS is to be believed, the *social* dimension is predominant on the official Instagram accounts of sports organizations, with *Behind-the-scenes* content alone accounting for over 3/4 of all posts (Doyle and al, 2020 ; Geurin-Eagleman and al., 2016 ; Smith and Sanderson, 2015). Off-stage contents that most increase engagement are aligned with athletes' and team branding and feature their off-game athletic lifestyle. *Behind-the-scenes* interaction between players, with two or several teammates, leads to higher engagement (Doyle and al., 2020). The *social* dimension also contains *Sweepstakes*, *Promotions* and *Crowdsourcing* which invite fans to react through networks (Subramani and Rajagopalan, 2003). Such content increases both likes and comments. As well as having an immediate positive impact on sales, they also have a positive influence on consumer brand loyalty and perception of the brand (Chandon, 1995 ; Coelho and al., 2016). Lastly, also categorized under the social umbrella, *social spotlight*, in which fan-generated content is put in the spotlight (Nepomuceno and al., 2020) also drives engagement, provided that certain conditions are met. High quality photos from fans outperform poor photos, and outperform professionally shot pictures, which consumers perceive as inauthentic (Doyle and al., 2020).

2.4.3 Quality dimension

Concepts akin to the *quality* dimension (Nepomuceno and al., 2020) have been explored by other researchers, such as self-oriented content (Kim and al., 2015), organization branding (Gavilanes and al., 2018), transformational message strategy (Tafesse and

Wien, 2018) and expressive value appeal (Johar and Sirgy, 1991). Quality-driven posts showcase the brand's experience, identity, values, and symbolic or hedonic features, through an *immersion* into the brand's universe, or through images and artful videos (Nepomuceno and al., 2020 ; Tafesse and Wien, 2018). It improves consumer perceptions of the brand and purchase decisions towards it, but only when the level of quality promoted matches the actual quality of the brand, and of the products or services it sells. The dimension is even more effective with non-informed consumers, i.e., consumers who consult only a single information source (Kopalle and al., 2017).

There are several subdimensions to the *quality* dimension, one of which is the valence of the content, a construct akin to *Joyful* (Nepomuceno and al., 2020), used in this research. Contrary to popular belief, content that is positive is more viral than negative content (Berger and Milkman., 2012). Of all content types, entertaining, funny, or exciting publications are found to be most influential, increasing engagement in likes, comments, and shares (Park and Lee, 2009). *Quality* is not just conveyed through words, but also through images. According to Li and al (2020), artistic and high-quality images and videos have been linked to higher levels of engagement.

2.4.3.1 Quality dimension on Facebook

On Facebook, there is no clear consensus on the effects of *quality* on engagement. Tafesse and Wien (2018) claim that *quality* posts create a strong emotional connection with consumers, increase online engagement, and even facilitate brand incorporation in self-perception. However, Dhaoui's (2014) research contradicts their claims by stating that *quality* posts decrease all engagement metrics. Among luxury brands, if some practices are not well received such as *Bridging* with celebrities, others have a positive impact on engagement such as posts presenting the performance or rarity features of the brand or its products (Dhaoui, 2014). *Quality* claims do not get the same reaction in different brand communities, depending on the brand equity and because the contents posted by companies vary. If on Twitter, textual content is predominant, yet on Facebook, almost three quarters of the posts made by companies include an image (Kim and al.,2015).

2.4.3.2 Quality dimension on Twitter

On Twitter, considering their scarcity, the addition of human imagery to text, drives shares and likes (Li and al., 2020). Celebrity faces are therefore received more favorably. On Twitter, using *Bridging*, which enables companies to engage in what interests their followers, right now, via posts linked to other domains or networks, such as celebrities but also social influencers and popular events like news or holidays increases retweets by 41 % (Malhotra, 2012 ; Nepomuceno and al., 2020 ; Viamark, 2010). Each SNS has its own audience, culture, and infrastructure.

2.4.3.3 Quality dimension on Instagram

Instagram is qualified by its users as a place to *pass the time* (Voorveld and al., 2018). Ideal for passing the time, high performance by athletes drives engagement (Doyle and al, 2020). However, publications with a central theme of branding and event coverage negatively impact comments and likes. Similarly, *Bridging to Holidays* (National Awakening Day, Labor Day, National Education Day, Eid al-Fitr, the Ascension of Jesus), which does not appeal to everyone, has the same adverse effect.

2.4.3.4. Quality dimension in short

A literature review of this issue leads to more questions than answers. If findings are so contradictory, it is mainly because samples and methodologies differ. The selection of moderating variables and platforms leads to significant variations in the results. Above all, comparing one author to another is arduous, because there is no single model and terminology for the segmentation of content. For instance, discussing weather on brands' official SNSs sometimes qualifies as unprofessional content (Devereux and al., 2020), gossip (Nepomuceno and al., 2020), entertaining content (Pletikosa Cvijikj and al., 2013), and interaction-oriented content (Kim and al., 2015). Our study aims to fill these gaps by connecting a content classification created by Nepomuceno and al. (2020), testing it in the field, and comparing our results to the existing literature, acting as platform comparators, and meaning translators.

Chapter 3 - Methodology

The main objective of this study is to test research questions regarding which types of contents engage consumers and which ones repel them, as well as their variation across social networks as listed in Chapter 1.

This chapter details the methodology used to answer these questions. It is organized into four sections : (a) selection of sports organizations (from the sample), (b) instrumentation and data coding, (c) fidelity and (d) data analysis.

3.1 Selection of Sports Organizations (sample)

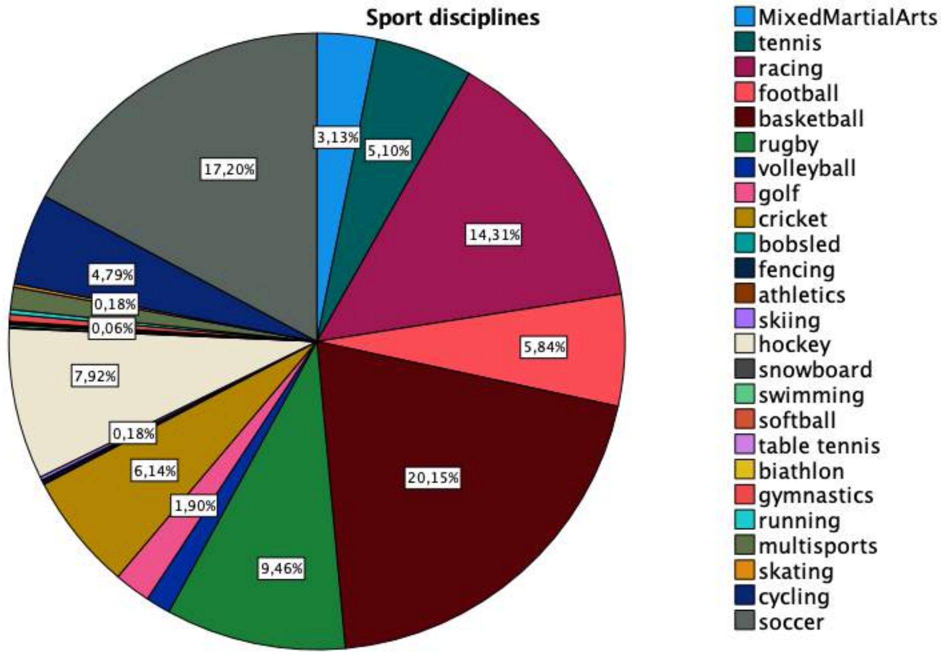
Our target population consists of professional sports organizations with an official page on Facebook, Twitter or Instagram. They include leagues or federations (e.g. WWF), teams (e.g. the Canadians), official competitions (e.g. the Tour de France), whether they are affiliated with a brand (e.g. the Ferrari team) or a geographical location (e.g. the Boston Red Sox). However, they exclude athletes' personal pages (e.g. Roger Federer) or sports brands (e.g. Nike's Jordan). Data on the number of professional sports organizations around the world is sparse. There are reportedly about 200 sports disciplines that belong to official federations or leagues (Wood, 2010). To obtain search results that can be generalized across professional sports organizations on social networks, we operated on the funnel principle by listing all sports found online and those that are part of our collective general culture. Collectively, since for this first step, our team is composed of two co-authors (one of whom will participate in the data collection and analysis), a coder and a research assistant who will only participate in this first step.

The choice of team members is deliberately diverse to avoid bias. Being a sports fan is an act largely defined by family and social context. The love of sports and the family team is traditionally passed down through generations, often from father to son. Fanaticism is rooted geographically (place of birth or residence) and even politically (the political identity that a team represents) (Tamir, 2020). Thus, it was essential that of the four team members, one had to be a woman. Their ages range over about twenty years and they come from four different continents.

From this first comprehensive list, that included all major existing sports, we then picked equal parts of team and individual sports. From there, we compiled the addresses of the federations', leagues', teams' and competitions' official Facebook, Twitter and Instagram pages. In our final selection, we chose those that had a minimum of 70,000 followers, prioritizing as many different sports as possible for representativeness, while endeavoring to keep a fair distribution of male, mixed and female teams.

This results in a sample of 233 different sports organizations, with 32.6 % coming from Twitter, another 32 % from Facebook and 35.4 % from Instagram. They average 9,497,852 followers. These organizations account for some 48 distinct sports, of which 83 % are either men's team or individual sports, while 6 % are either women's team or individual sports and the rest are mixed teams. Though basketball ranks first in the study in terms of the frequency of coverage, an estimated 70 % of the publications covered are individual sports. A little less than half of the disciplines studied, 45.8 %, entail a risk of body collision. 43.8 % of publications come from North American teams or organizations, the corresponding numbers being 5 % for those of a European source, 7.9 % from an Asian source, 4.7 % from an Australian source and 8.2 % from an international source other than those previously mentioned. As shown in the figure below, for the purpose of data analysis, the original 48 sports are divided into 25 categories.

Fig. 2 Distribution of sports in the sample



The 5,000 posts were obtained by Web scraping of social media, with scraper bots automatically collecting data online, from September 2019 to March 2020 (Salinas, 2021).

3.2 Instrumentation and data coding

Once the data were in hand, coding of the scraped data could begin. The instrument used to measure the variables of interest, as defined in our Theoretical Framework (i.e. FGC Dimensions, Consumer Engagement) is a grid developed in a previous study by Nepomuceno and al. (2020) (see Appendix A for coding grid information).

The two coders, marketing students, received detailed training on the coding instrument and set of categories by Prof. Nepomuceno, including exploratory content analyses (Nepomuceno and al., 2020). To achieve an inter-coder reliability score of 95 %, the grid was adapted. The main content dimensions as detailed in the grid, i.e., *architectural*, *selling*, *quality* and *social*, remained, but the subdimensions were reviewed and modified to fit the new field of observation.

At this stage, neither coder (nor even the co-author of the text) was aware of the purpose of the study, nor of the hypotheses that were being put forward.

Collaborative qualitative hand coding of the 5,000 messages was then performed. It was performed by the coders, including one of the authors (Zade and al., 2018). Each data instance was coded in a binary manner (1 = belongs to the category, 0 = does not belong to the category).

A Chinese wall was placed between the two coders to avoid a contamination of the results. The third step was to create an Excel macro to compare the results once the 5,000 posts were completed. Although all items were previously discussed, defined, and agreed upon by the coders and supervisor, once the results were compiled, their interdependent reliability scores were uneven. For all 31 columns, the interrelated reliability scores ranged from 34.57 % to 99.82 %, with an average of 86.40 %. All disagreements were discussed until a consensus was reached. When the coders could not reach a consensus, Professor Nepomuceno served as the referee and often made the final decision (Zade and al., 2018). An interrelated reliability score of 99 % or higher was then achieved for all instances. Appendix B, a document entitled Reliability discussions, details the numerous back-and-forths and the choices made in each category. Some screenshots are also included to facilitate the reading.

3.3 Fidelity

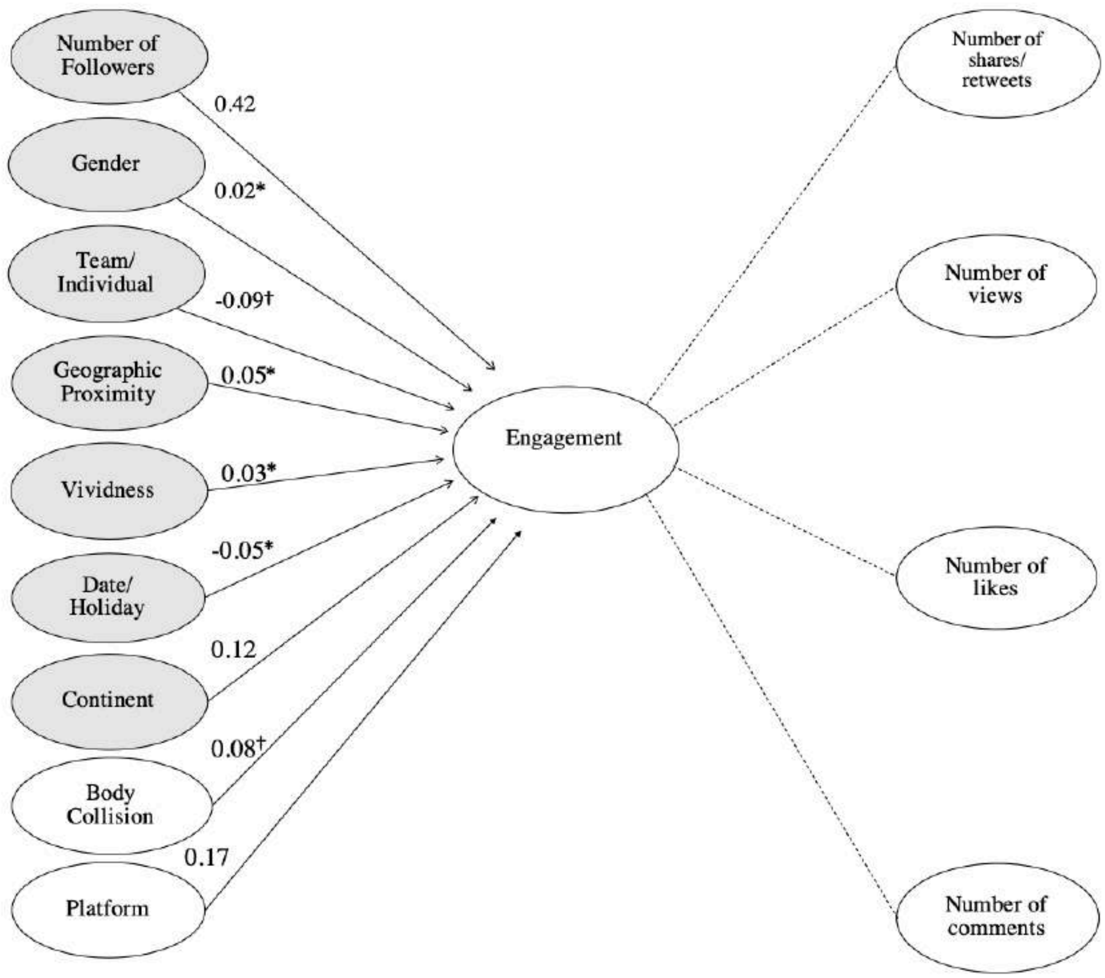
The formative model was chosen over the more common reflective model, where Alpha serves as an indicator for the quality of the instrument. Unlike Cronbach's Alpha, which focuses too much on homogeneity among the elements of a construct (the content subdimensions), the formative model combines several indicators to form a construct, with or without inter-correlation among its elements (Coltman and al., 2008 ; Stadler and al., 2021).

We chose the formative model for three reasons. First, our constructs, the dimensions (*architecture*, *selling*, *quality*, and *social*) and their indicators (the subdimensions) are composite measures, which do not exist as independent entities (Nepomuceno and al., 2020). Second, deleting any of the subdimensions could change the total dimension score and alter the empirical meaning of the construct. No two dimensions, two items, are interchangeable or have the same content (Coltman and al., 2008). Third, because the subdimensions all impact the primary dimensions. They act as influencers rather than influencees. Thus, they may be correlated or completely uncorrelated. In the case of this study, they are often uncorrelated (Borsboom and al., 2003 ; Coltman and al., 2008).

3.4 Data analysis

Originally, quantitative data analysis includes numerical scores obtained from 48 binary coded items, (1 = belongs to the category, 0 = does not belong to the category). Thus, to know the number of publications where there is a specific subdimension, take the example of Explicit Selling, one would simply add up all the 1s in the *Explicit Selling* category. These 48 items were then grouped into four different constructs : architectural (18), *selling* (9), *quality* (12) and *social* (9). In addition to the content dimensions, we combined and added items to test additional constructs. We assigned a vividness score according to the type of content (text, photo, video, animation) from 1 to 4. We divided sports according to the presence (1) or absence (0) of *body collision* risk and coded SNS from 1 to 3 to make it a moderator. We also divided sports organizations by gender and their association with a city, state/province/country, brand, or league/federation. Once the constructs and items were added, a preliminary model was tested through multiple regressions in the SPSS program.

Fig. 3 Preliminary Model



* Significant at .05 or lower, † marginally significant (p<.10)

Body Collision (Mitchell, 1985) was chosen as a moderating variable since it has the greatest influence on the relationship between the predictors and the outcomes of the model. The significance level was set at $p \leq 0.05$ for the ANOVA. Three of the four content dimensions were kept as independent variables ; the *architectural* dimension was not retained at this stage.

Different measures of engagement were tested as dependent variables but only likes and comments were retained. Shares, retweets and views had too much missing data from one SNS site to another.

Table 1Missing data

	N	Missing	% Missing
# of Followers	4,947	52	1.04
# of Views	1,037	3,962	79.26
# of Comments	4,941	58	1.16
# of Likes	4,875	124	2.48
# of Shares	3,123	1,876	37.53

The variables – Followers / Gender / Team or Individual / Geographic proximity / Vividness / Holiday / Continent / Body collision / SNS - were tested through numerous regressions to see if they significantly altered the influence of content on the number of Likes and Comments. Since the number of followers have an undeniable influence on engagement in the study, we introduce a new variable.

Indeed, to limit the influence of the size of the community, organization or a discipline over another, the number of likes and comments is divided by the number of followers, which we call *relative likes* and *relative comments.* The number of followers thus becomes a control variable.

Table 1 Linear relationship between followers and likes and comments

Correlations

Followers	**Likes**	**Comments**
Pearson Correlation	.45**	.31**
Sig. (bilateral)	<.001	<.001
N	4,823	4,889

By correlating likes and comments on followers, without distinguishing between SNS, we find a moderate positive relationship in both cases for likes and comments ; these results are highly significant.

The Holiday variable had an undeniable moderating influence on the relationship between content and engagement. However, among the 5,000 publications collected, Holidays are overrepresented with over 50% of the dates identified as such.

Body collision and the choice of SNS are the two variables with the most significant moderating effect. Therefore, they were chosen as the moderating variables of the model. Based on previous research and our preliminary observations, it is relevant to keep the following five control variables constant through linear regressions :

1. Gender (masculine/feminine)
2. Team/Individual sport
3. Geographic proximity to fan communities (Local/National/International/Privately owned teams)
4. Vividness (Text/Photo/Video/Animation)
5. Continent
6. If the posts were published on a Holiday or not (Christmas, Thanksgiving, Valentine's Day)

In short, this chapter reinstated the purpose of this research and presented the research questions. The choice of sports organizations selected from the target population was discussed. Furthermore, the validity and reliability of the measuring instruments were presented. Lastly, the data analysis methods and the choice of variables were presented. The study's findings are presented in the following chapter.

Chapter 4- Study's Findings

4.1 Introduction

The objective of this study was to examine the interrelationships between companies' choice of content and choice of SNS on the engagement of its online consumers. The objective was achieved by examining the explanatory power of combined models including three different content dimensions (*selling*, *quality*, *social*) and three SNSs (Twitter, Facebook, Instagram) on two engagement measures (*relative likes*, *relative comments*). The moderating effect of *body collision* was added to this model to gain further insight into the differences across sports. This section presents the results of the data analysis for the four stated research questions. The descriptive statistics, including univariate and bivariate statistics, were first reported, then followed by the results of linear regressions, and finally by the results of logistic regressions with a moderator performed with the PROCESS modeling tool by Andrew F. Hayes v 3.5. (Haynes, 2021).

The results are organized according to the four research questions. The descriptive statistics were used to answer the first research question, "***What dimension of content do sports companies predominantly use on their official social networks ?***"

The linear regressions provided the results for the second research question, "***To what extent are the different dimensions of content generated by sports organizations associated with consumers' engagement on their official SNS ?***"

PROCESS was utilized to answer the third and fourth research questions, "***How does the risk of body collision in sport impact the relationship between the content dimensions of the FGC and the CE ?***" and "***To what extent are the different subdimensions of content generated by sports organizations associated with consumers' engagement on their official SNS? How does the risk of body collision in sport impact the relationship between the content subdimensions of the FGC and the CE ?***".

4.2 Descriptive Statistics

To gain a general understanding on how variables are distributed, we first investigated the descriptive statistics. By looking at them, we first noticed that several variables are very dispersed, leading to a large variance and standard deviation.

4.2.1 Log10

For instance, looking at the number of followers, the group's average number of followers is 8,607,041 and the median 1,500,000 followers. With a variance of 101,128,294 and a standard deviation of 16,235,975, the mean is far from indicative of the whole dataset. The smaller values are overwhelmed by the larger values. In a normal distribution, about 68 % of the values are within one standard deviation either side of the mean.

In our sample, our engagement performance measures (likes, comments, shares, views) have a large variance and do not respect that percentage. This results in highly positively skewed distributions (skewed to the right). Since it is preferable for those variables to be in a normal distribution before performing our regressions, we normalized them through a log10 transformation and created new variables. Looking at the logarithm, the visualization becomes clearer (Galili, 2013 ; Metcalf and William, 2016).

Except for a few cases where we compare the data before and after the transformation, all graphs show likes and comments after the Log transformation. To make it easier to read, we did not add *after Log* each time.

Below, two examples of distributions before and after the Log transformation.

Fig. 4 *Relative likes* before Log10

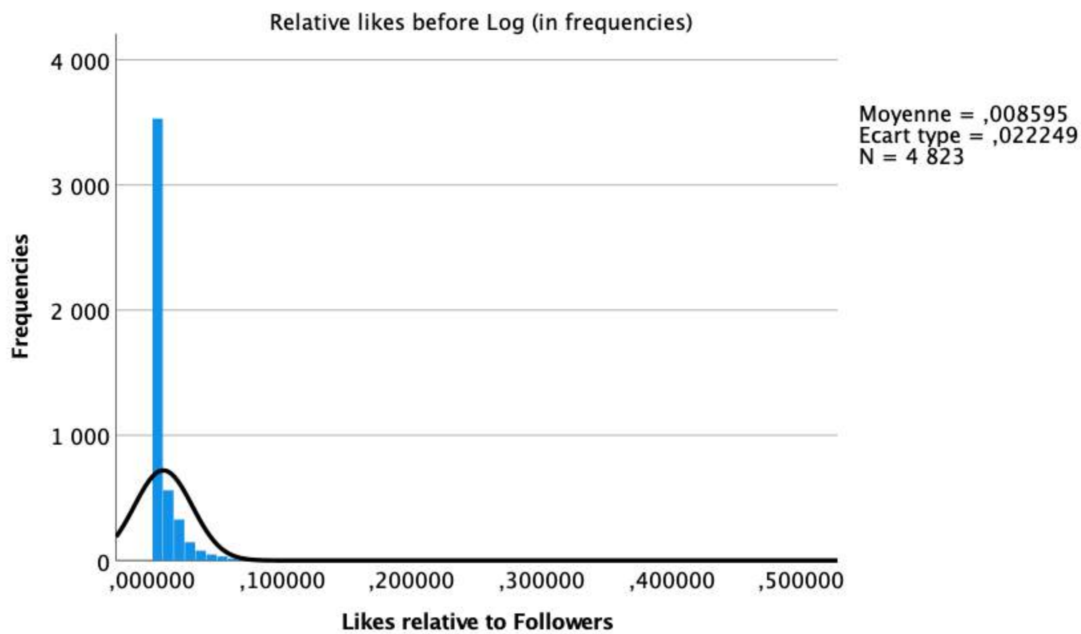


Fig. 5 *Relative likes* after Log10

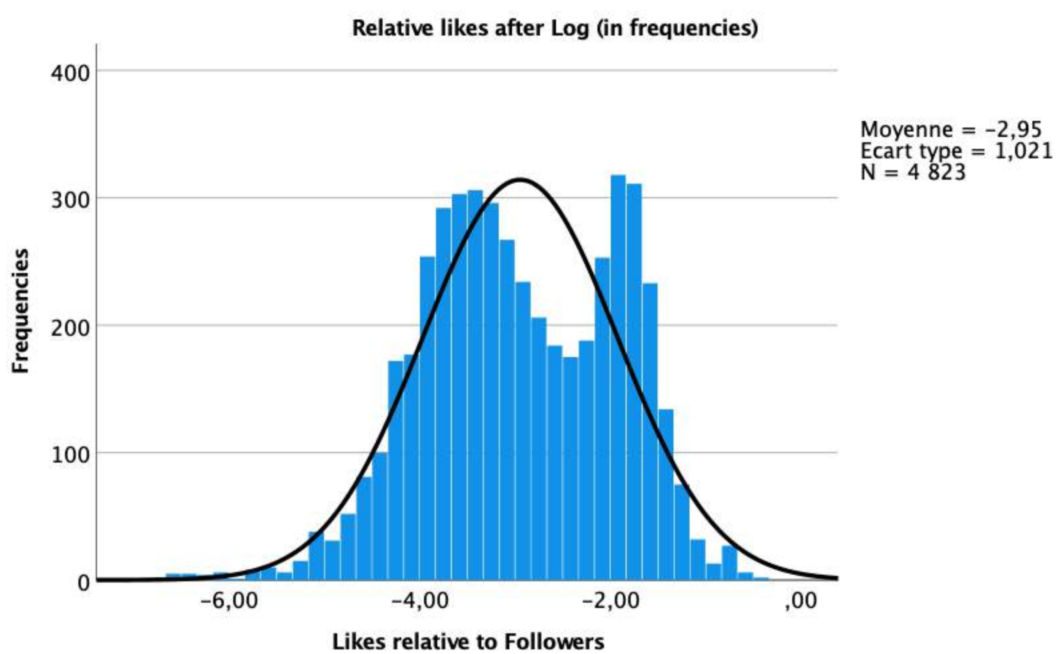


Fig. 6 *Relative comments* before Log10

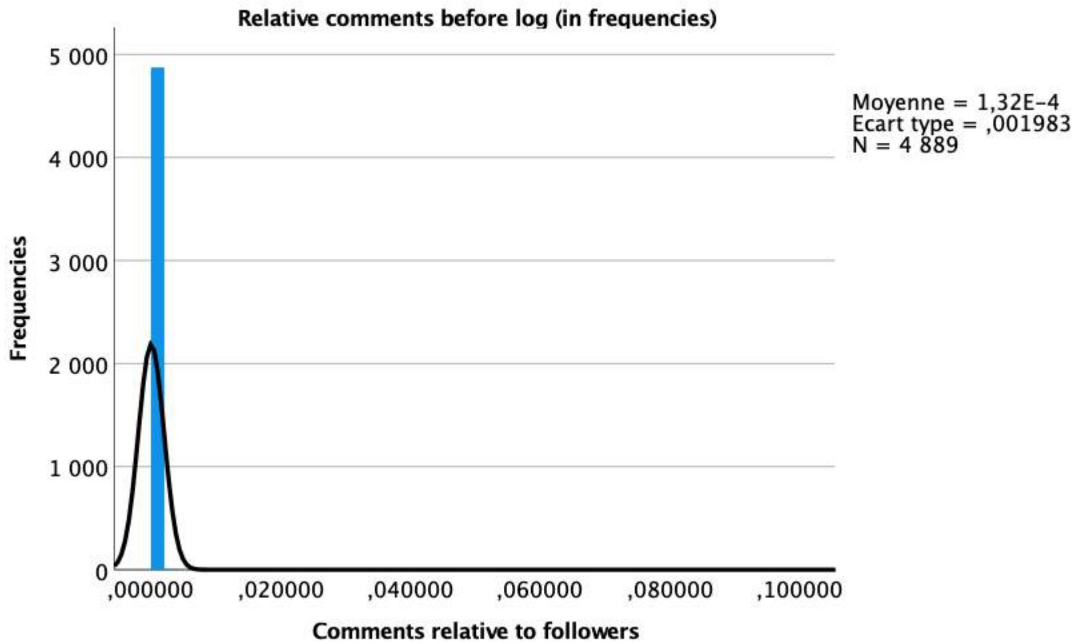


Fig. 7 Comments before Log10

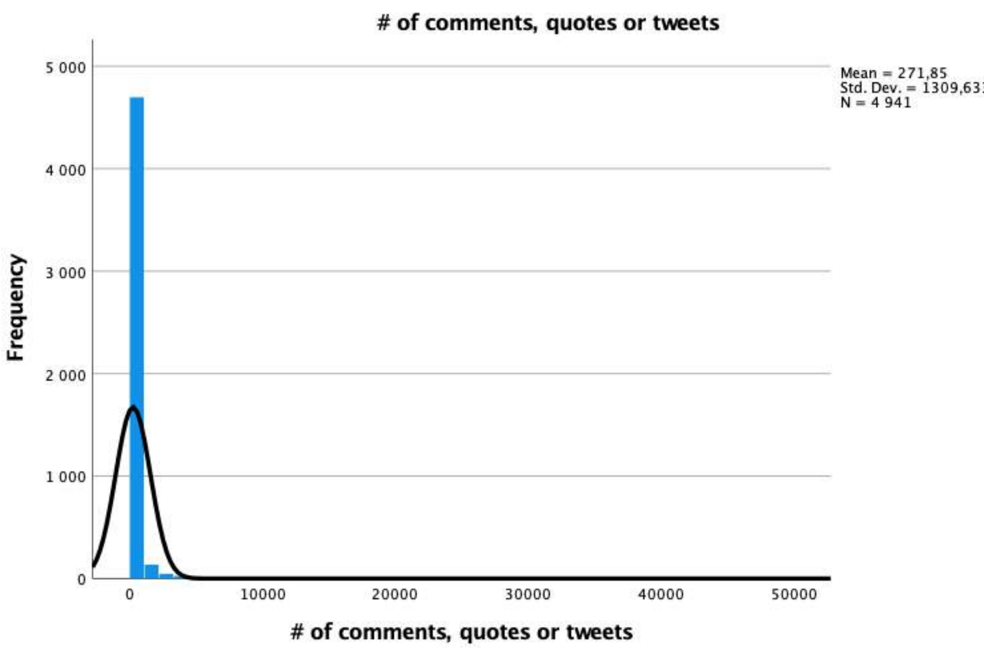
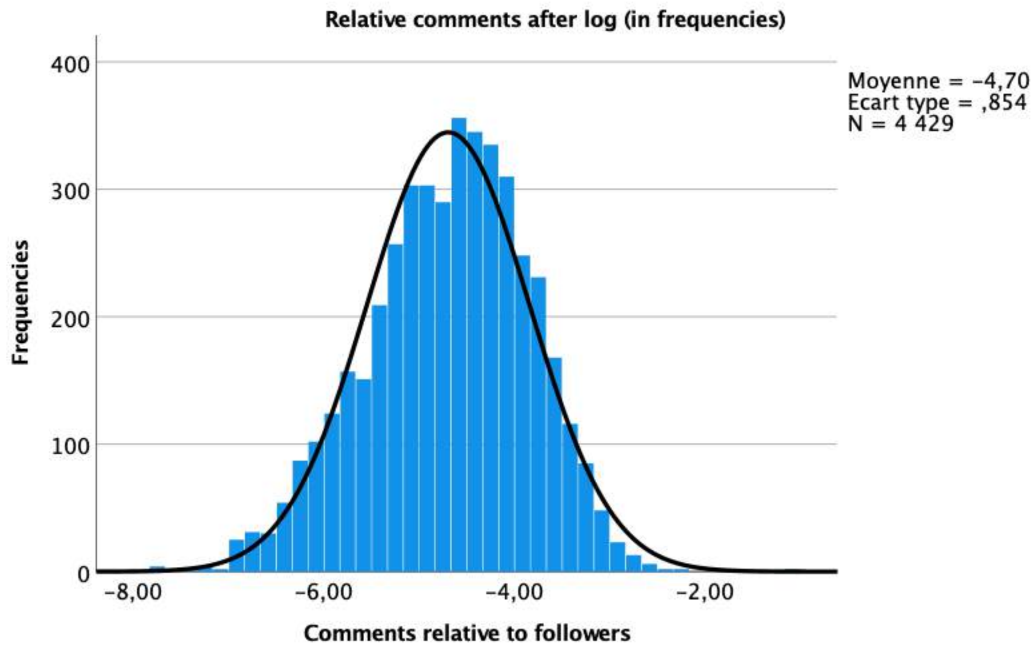


Fig. 8 *Relative comments* after Log10



4.2.2 Sample

Certain demographic statistics about the organizations in the sample are noteworthy. It is significant that over 55 % of the organizations are North American and that over 77 % of them represent male teams or athletes.

A glance at frequencies also reveals that organizations' content posted on SNS is highly vivid. Of the content retrieved, more than 94 % contains either a photo, video, animation, or carousel.

Table 3 Univariate analyses of *Geography*

	N	%
Asia	256	5.1
Australia	175	3.5
Europe	1,436	28.7
North America	2,762	55.3
World	370	7.4
Total	**4,999**	**100**

Table 2 Univariate analyses of *Gender*

	N	%
Masculine	3,884	77.7
Feminine	316	6.3
Both (practiced by both genders separately)	720	14.4
Mixed (practiced in mixed teams)	71	1.4
Total	**4,991**	**99.8**

Table 3 Univariate analyses of *Vividness*

	Valid	N	%
Text	4,999	4,981	99.60
Photo/Image	4,999	2,465	49.30
Video	4,999	1,862	37.20
Animation	4,999	27	0.5
Carousel	4,999	368	7.4

4.2.3 Engagement rates

There are several ways to measure engagement. Engagement rate is one of the most used metrics to assess the degree of user involvement with content and the health of the community (the degree of reactivity and number of "real" followers).

Engagement is essentially a measure of how often a quantity of users interact with a brand (Chen, 2021). Using the compute variable function in SPSS, we calculated the engagement rate for each of the SNSs and created new variables (EngaTw/EngageFa/EngagIns). The engagement rate is calculated as : overall user engagement (total number of likes, comments, and shares, depending on the availability of information), divided by the total number of followers, multiplied by 100 (to get a percentage). For example, if the total engagement for a given month is 3,600 (3,000 likes + 400 shares + 200 comments) and the total number of followers for that month is 110,000 the engagement rate is (3,600/110,000) *100 = 3.27 % (Niciporuc, 2014 ; Vora, 2018).

The engagement rates of our sample are significantly higher than those reported by all industries in literature, excluding the sports industry, which performs significantly better.

For Twitter, while the sports industry reports on average engagement rates around 0.07 %, in our sample we see rates twice as high. Over on Instagram, in our sample they are 1.5 times higher than the average rates of 1.79 %. And on Facebook, they are 1.34 times higher than the industry rates of 0.12 % (Feehan, 2021).

Table 4 Engagement measures

	N	Missing	Mean	Mode	Std. Deviation
# of Followers	4,947.00	52.00	8,607,041.32	1,200,000.00	16,235,975.27
# of Views	1,037.00	3,962.00	337,787.28	2,900.00	951,487.02
# of Comments	4,941.00	58.00	271.85	0.00	1,309.63
# of Likes	4,875.00	124.00	33,723.45	1,100.00	125,127.66
# of Shares	3,123.00	1,876.00	313.07	1.00	1,305.21

4.3 Testing the Research Questions

To address the first research question, we retrieved the frequency tables for each of the content dimensions, across all SNSs. Then we repeated the process, this time by splitting the data base into different platforms to compare them. Then we dug a little deeper and extracted tables of frequencies for the subdimensions. Eventually, we produced some bar charts to better visualize the results.

4.3.1 Research Question 1

"***What dimension of content do sports companies predominantly use on their official social networks ?***"

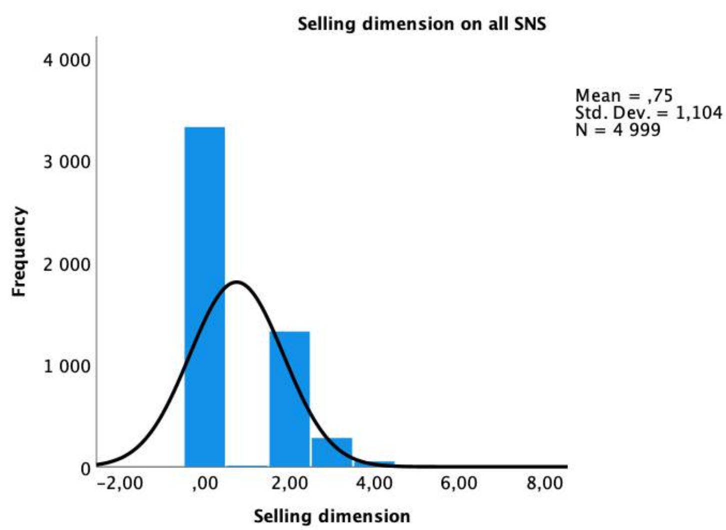
Selling across all SNS

Table 5 *Selling* frequencies on all SNS

Selling on all SNS

Level	**N**	**%**
None	3,323	**66.5**
1	**10**	**0.2**
2	1,324	26.5
3	282	5.6
4	52	1
5	**6**	**0.1**
6	**1**	**0**
7	**1**	**0**
Total	**4,999**	**99.9**

Fig. 9 *Selling* frequencies on all SNS



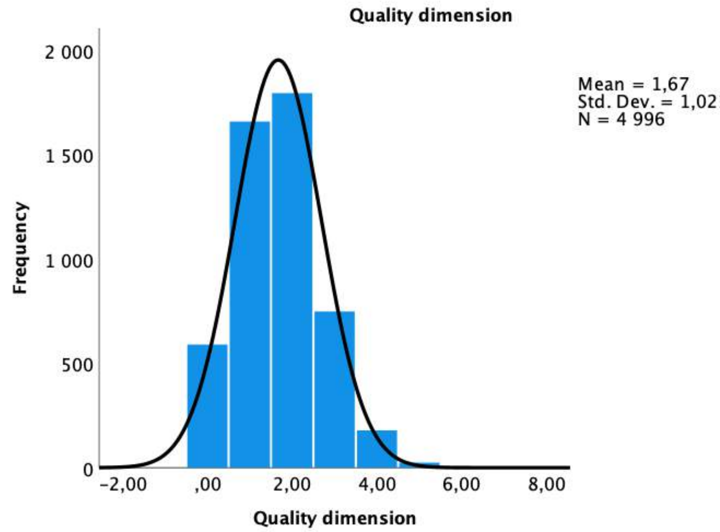
Quality across all SNS

Table 6 *Quality frequencies* on all SNS

Quality on all SNS

Level	N	%
None	590	11.8
1	1,658	33.2
2	1,794	**35.9**
3	748	15
4	179	3.6
5	**24**	**0.5**
6	**3**	**0.1**
Total	**4,996**	**100**

Fig. 10 *Quality* frequencies on all SNS



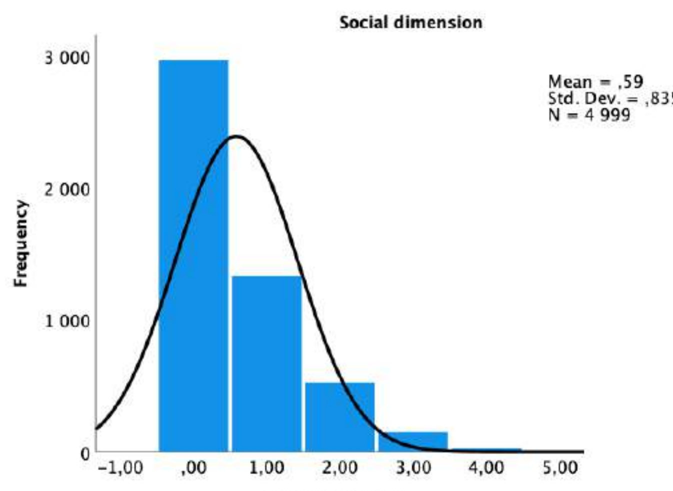
Social across all SNS

Table 7 *Social* frequencies on all SNS

Social on all SNS

Level	N	%
None	2,969	**59.4**
1	1,329	26.6
2	523	10.5
3	152	3
4	**26**	**0.5**
Total	**4,999**	**100**

Fig. 11 *Social* frequencies on all SNS



When considering the three social networks together, the dimension most used by sports organizations is the *quality* dimension. 88.2 % of all posts listed contained at least one marker, one subdimension of the *quality* construct. Comparatively, only 40 % of the publications would broadcast *social* and 33 % *selling*.

Selling frequencies by SNS

Table 8 *Selling* frequencies on Twitter

Level	N	%
None	1,127	**69.2**
1	5	0.3
2	352	21.6
3	114	7
4	26	1.6
5	**2**	**0.1**
6	**1**	**0.1**
7	**1**	**0.1**
Total	**1,628**	**100**

Table 9 *Selling* frequencies on Facebook

Level	N	%
None	960	**60**
1	**2**	**0.1**
2	514	32.1
3	100	6.3
4	19	1.2
5	**4**	**0.3**
Total	**1,599**	**100**

Table 10 *Selling* frequencies on Instagram

Level	N	%
None	1,236	**69.8**
1	**3**	**0.2**
2	458	25.8
3	68	3.8
4	**7**	**0.4**
Total	**1,772**	**100**

The results are quite similar from one network to another. Of the three networks, Facebook is the one where organizations post the most *selling*, nearly 10 % more (39.96 % compared to 30.46 % for Twitter and 30.25 % for Instagram).

Quality frequencies by SNS

Table 11 *Quality* frequencies on Twitter

Level	N	%
None	191	11.7
1	571	35.1
2	580	**35.6**
3	227	14
4	52	3.2
5	**6**	**0.4**
Total	**1,627**	**100**

Table 12 *Quality* frequencies on Facebook

Level	N	%
None	220	13.8
1	493	**30.8**
2	535	33.5
3	249	15.6
4	89	5.6
5	**12**	**0.8**
6	**1**	**0.1**
Total	**1,599**	**100**

Table 13 *Quality* frequencies on Instagram

Level	N	%
None	179	10.1
1	594	33.6
2	679	**38.4**
3	272	15.4
4	38	2.1
5	**6**	**0.3**
6	**2**	**0.1**
Total	**1,770**	**100**

To share *quality* related messages about their organization, sporting organizations use the three platforms extensively. On Instagram, nearly 90 % of publications have *quality* as an attribute ; the corresponding percentages are 88 % for Twitter and 86 % for Facebook.

However, one post may correspond to multiple *quality* subdimensions. Therefore, a *quality rating* may be created. Compiling all of these scores, Instagram is still in the lead, followed by Facebook in second place and Twitter in third.
Although there are more publications that use *quality* on Twitter, there are more posts that match more than one subdimension at a time on Facebook.

Social frequencies by SNS

Table 14 *Social* frequencies on Twitter

Level	N	%
None	1,042	**64**
1	415	25.5
2	135	8.3
3	33	2
4	**3**	**0.2**
Total	**1,628**	**100**

Table 15 *Social* frequencies on Facebook

Level	N	%
None	983	**61.5**
1	379	23.7
2	177	11.1
3	46	2.9
4	**14**	**0.9**
Total	**1,599**	**100**

Table 16 *Social* frequencies on Instagram

Level	N	%
None	944	**53.3**
1	535	30.2
2	211	11.9
3	73	4.1
4	9	0.5
Total	**1,628**	**100**

When it comes to *social,* the variations between platforms are more marked. Sports organizations use it relatively seldom on Twitter with only 36 % of all publications linked to it ; the percentage climbs to nearly 39 % on Facebook and ultimately reaches nearly 47 % of all publications on Instagram. The associated *social ratings* are in the same order.

Subdimensions

Selling subdimensions frequencies across all SNS

Table 17 *Selling* subdimension frequencies

	Valid	N	%
Explicit Selling	4,999	162	3.24%
Implicit Selling	4,999	1,520	30.41%
Product Family	4,999	154	3.08%
Price	4,999	7	0.14%
Subscriptions	4,999	44	0.88%
Event Marketing	4,999	50	1.00%
Events Tickets	4,999	1,137	22.74%
Prize Draws	4,999	71	1.42%
CrossPromotion	4,999	612	12.24%

In terms of *selling* subdimensions, we see very little *Explicit Selling* - hard sales. The most frequent publications are announcements of events, usually upcoming sports matches - they are regularly coupled with *Implicit Selling* (posts that implicitly sell a specific game, product, or subscription) together they account for 53 % of *selling* publications.

Quality subdimension frequencies across all SNS

Table 18 *Quality* subdimension frequencies

	Valid	N	%
Production	4,999	**5**	**0.10%**
Development	4,999	264	5.28%
Hooking	4,999	903	18.06%
Statistics	4,999	317	6.34%
Immersion	4,999	146	2.92%
Bridging	4,999	201	4.02%
Bridging People	4,999	83	1.66%
Healthy	4,999	**7**	**0.14%**
Joyful	4,999	1,549	30.99%
News	4,998	1,253	25.07%
Gallery	4,997	2,744	54.91%
Highlights	4,999	874	17.48%

Sports organizations publish a lot of photos and videos of sports performances. *Highlights* are recent and depict a moment of victory. Artistically different photos and videos (a blurred background, a filter, the choice of lighting, the choice of aperture) displaying a high performance, are rather under *Gallery*. These two categories represent 72.39 % of all *quality* instances.

Social subdimension frequencies across all SNS

Table 19 *Social* subdimension frequencies

	Valid	N	%
Bonding	4,999	630	12.60%
Evangelization	4,999	**3**	**0.06%**
Defending	4,999	91	1.82%
Social Spotlight	4,999	**25**	**0.50%**
Small Talk	4,999	74	1.48%
Intimacy	4,999	408	8.16%
BehindtheScene	4,999	1,011	20.22%
Crowdsourcing	4,999	576	11.52%
Charity	4,999	117	2.34%

Behind-the-scenes and *Intimacy* account for almost 30 %. The two subdimensions are different, one is always out of the game, whereas the other may take place in the players' home as well as on the field. The intention however is the same, to create a feeling of proximity between an organization and its fans.

In short, the most used content dimension by sports organizations is the *quality* dimension. They used it on all their SNS in over 88 % of publications. Highlights and artistic photos and videos account for 72 % of all the *quality* posted by those organizations.

4.3.2 Research Question 2

To address the second research question : ***"To what extent are the different dimensions of content generated by sports organizations associated with consumers' engagement on their official social networking sites ?"*** we tested the impact that each content dimension has on each engagement measure through 18 different linear regressions. To do so, we selected one SNS at a time with data-select case. One linear regression at a time, we were careful to include the control variables. When we found meaningful relationships, those with p-values ≤ 0.05, we graphically illustrated them.

Table 20 Impact of content dimensions on CE on Twitter

Results of Linear Regression Analyses by Content Dimensions on Twitter

	N	*RNG*	*M*	*S.D.*	B	β	*t*	*p*	R^2
Sell. on likes	1,628	12	0.74	1.21	-0.13	-0.21	-9.16	**0.00**	0.23
Sell. on comments	1,628	12	0.74	1.21	-0.12	-0.19	-7.07	**0.00**	0.24
Qual. on likes	1,627	5	1.62	0.99	0.10	0.14	5.67	**0.00**	0.20
Qual. on comments	1,627	5	1.62	0.99	0.06	0.09	3.11	**0.00**	0.21
Soc. on likes	1,628	4	0.49	0.75	0.01	0.01	0.59	0.56	0.19
Soc. on comments	1,628	4	0.49	0.75	-0.05	-0.06	-2.00	**0.05**	0.21

The p-values (≤ 0.05) indicate that sports firms that post content with *selling*, *quality* or *social* dimension on Twitter have a significant impact on user online engagement (measured in likes and comments) on the measured sample, but also in the overall population. The only exception to this rule is *social* posting which has no significant impact on the number of likes. The r-squares of the 3 content dimensions are quite similar, 23.5 % for *selling*, 20.5 % for *quality* and 20 % for *social*.

The three dimensions therefore explain a similar part of the variance of the independent variables of our model : the likes and comments published by online users. However, if the percentages are similar, the interactions between the types of content and online engagement are not the same. The *selling* dimension decreases engagement whereas the *quality* dimension increases it and the *social* dimension shows no clear tendency. The beta coefficients in the *selling* dimension are negative. *Selling* dimension has a decreasing effect on both likes and comments as seen below on the scatter plots.

Fig. 12 Impact of *selling* on *relative likes* on Twitter

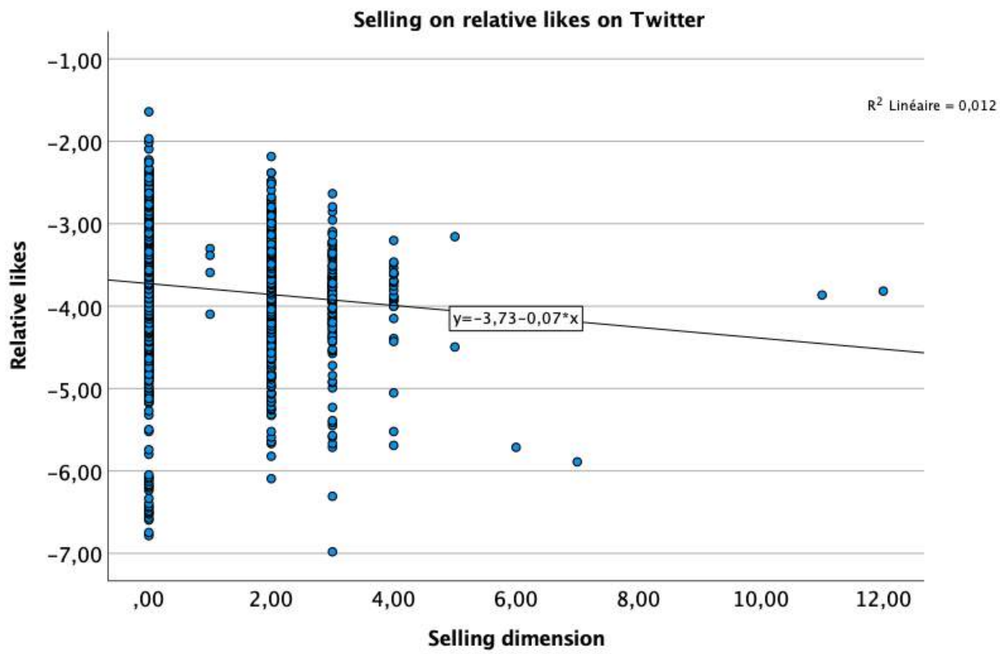


Fig. 13 Impact of *selling* on *likes* on Twitter

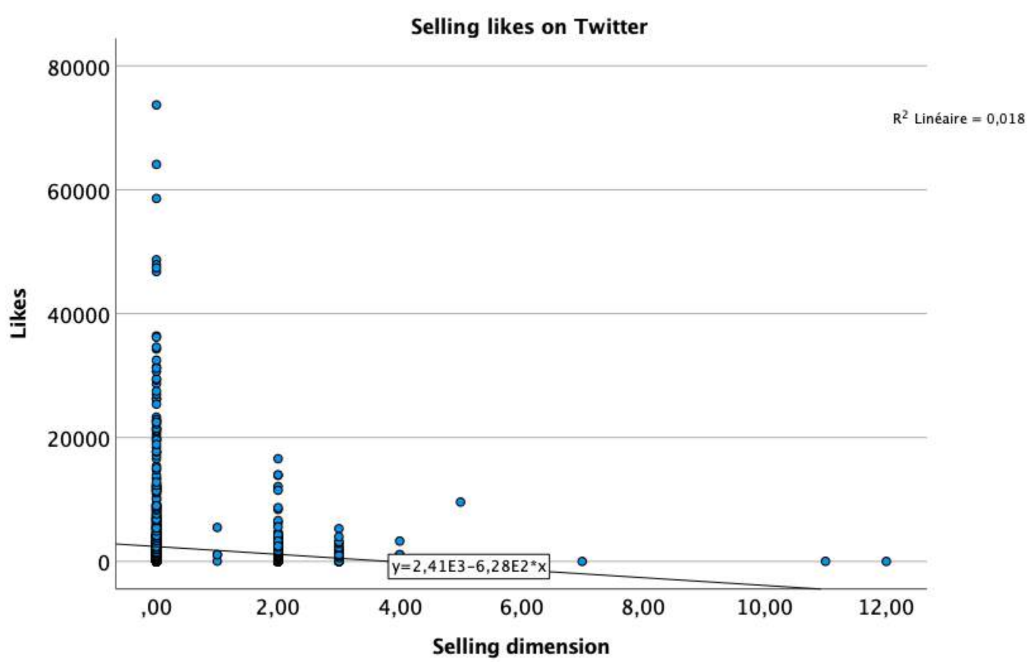


Fig. 14 Impact of *selling* on *relative comments* on Twitter

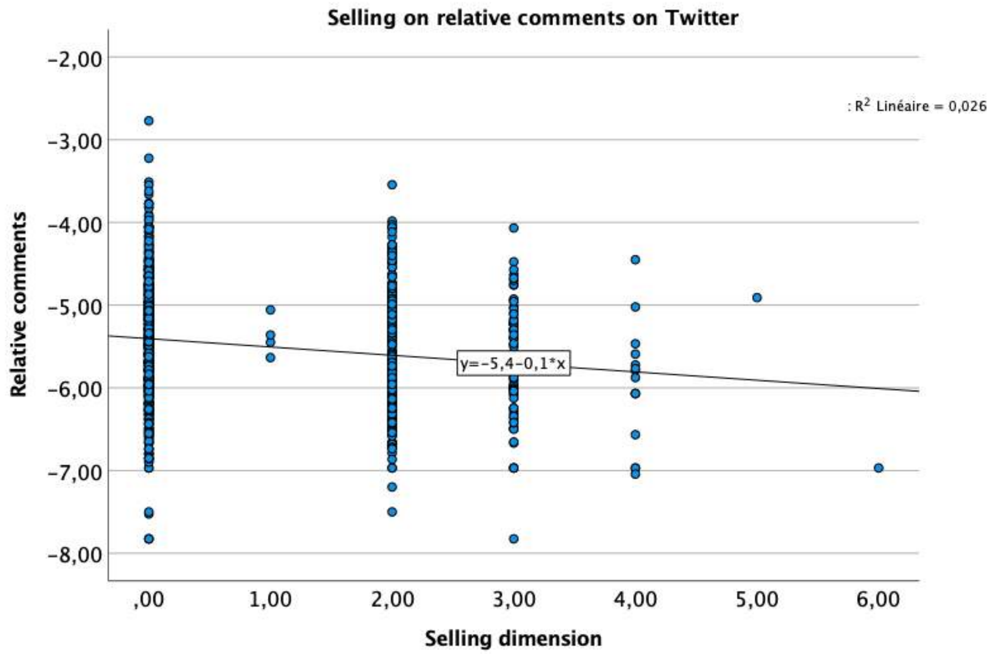
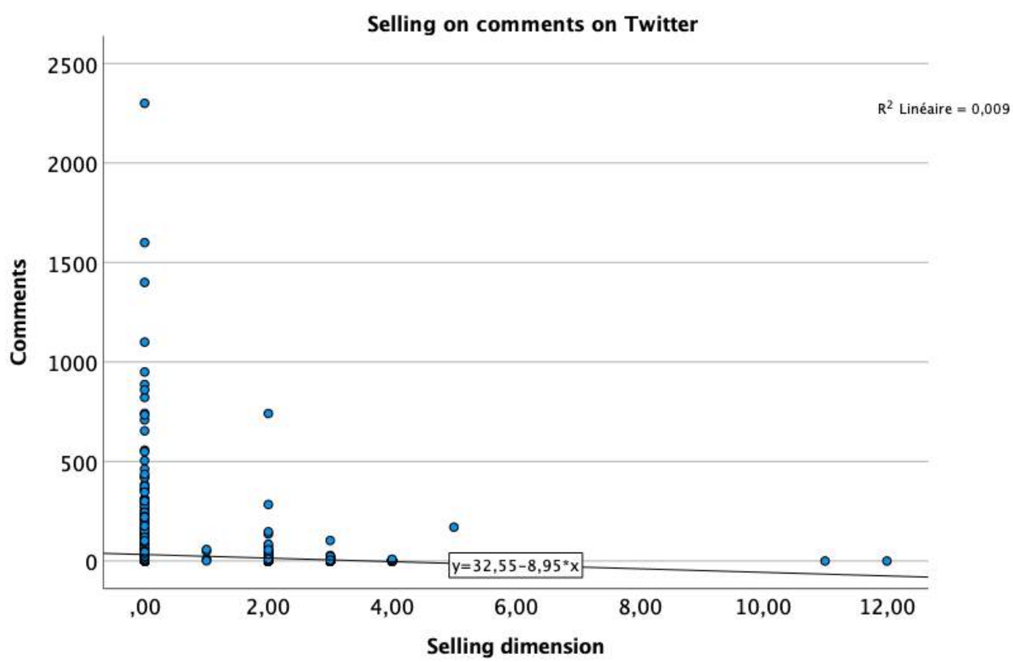


Fig. 15 Impact of *selling* on *comments* on Twitter



As for the beta coefficients in the *quality* dimension, they are positive. The increase of the *quality* dimension is associated with an increase of likes and comments on Twitter. The slope is steeper for likes than for comments. Thus, publishing *quality* increases comments and likes, the latter in a higher proportion.

Fig. 16 Impact of *quality* on *relative likes* on Twitter

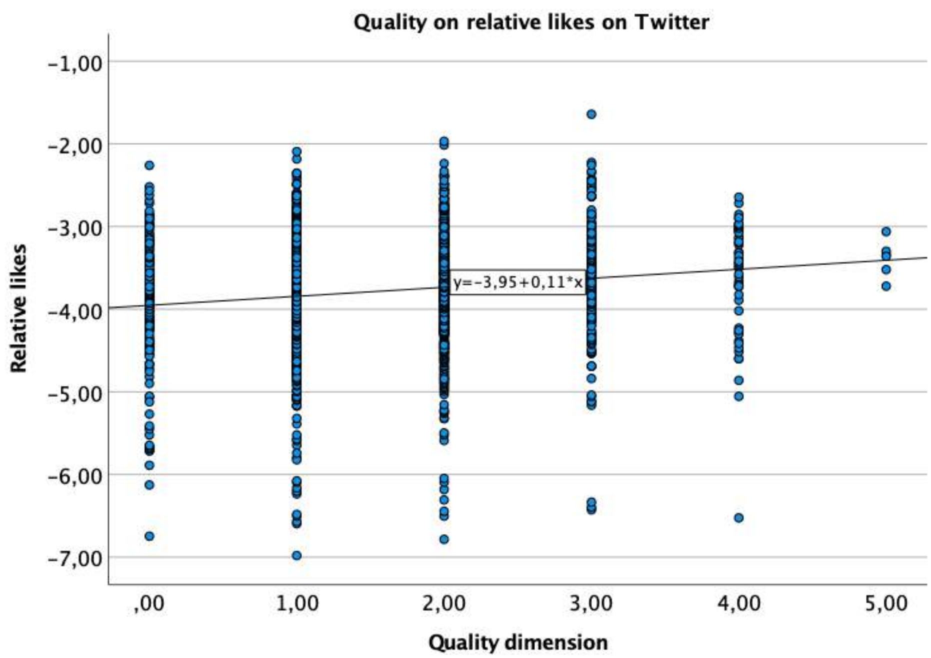


Fig. 17 Impact of *quality* on *likes* on Twitter

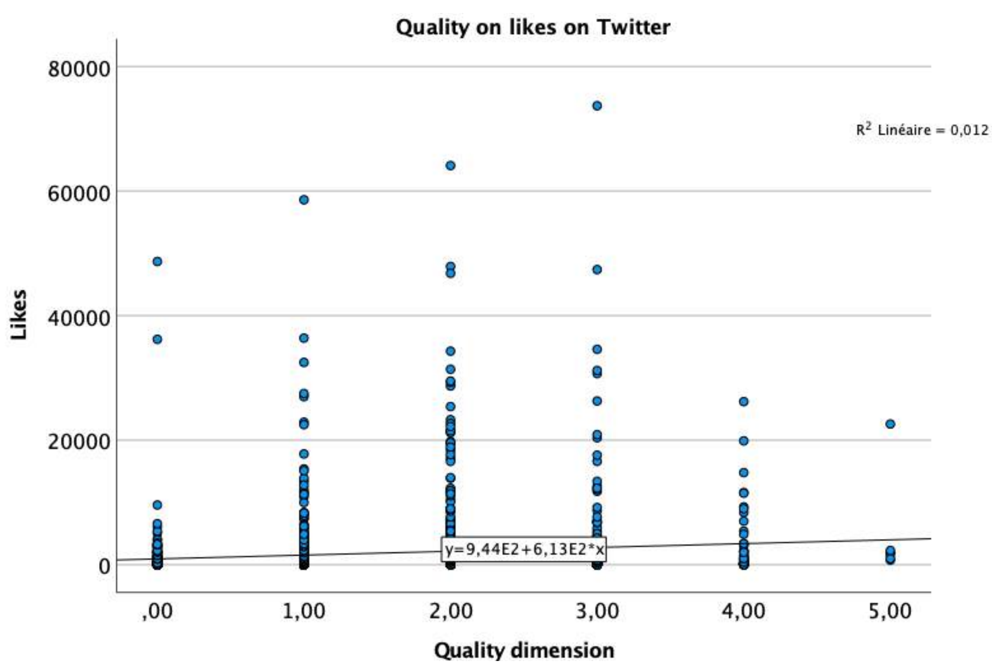


Fig. 18 Impact of *quality* on *comments* on Twitter

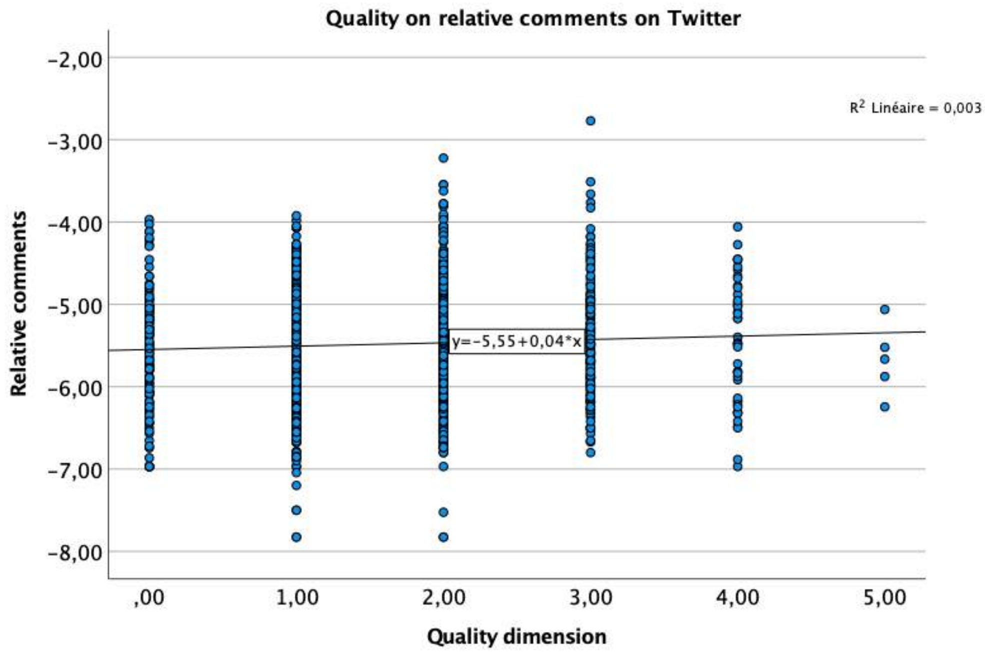
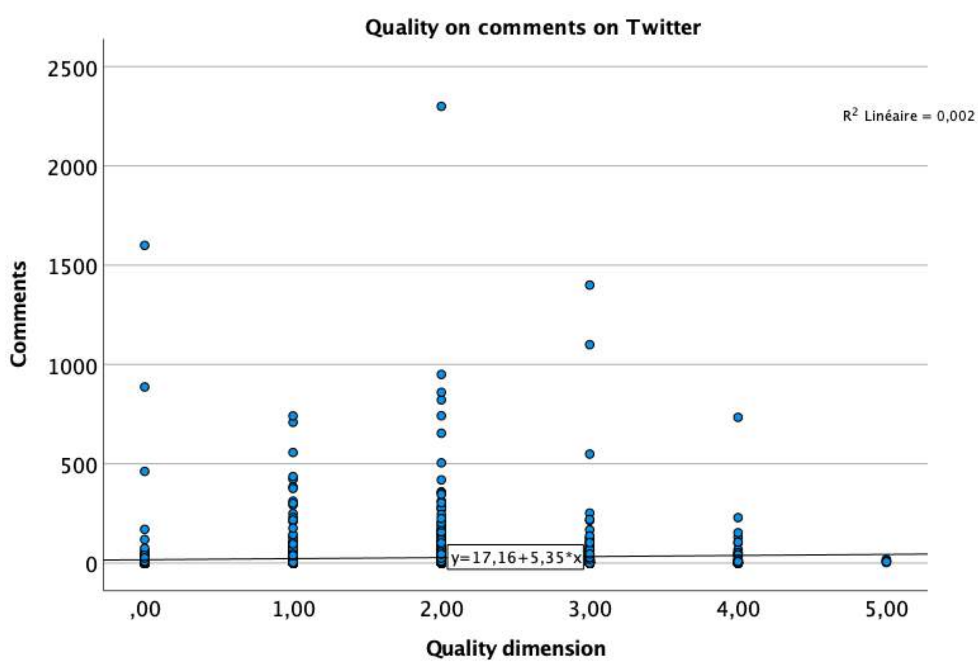


Fig. 19 Impact of *quality* on *comments* on Twitter



As for the *social* dimension on Twitter, p is significant only on comments. However, the scatterplot illustrates a regression slope very close to zero. Displayed are almost a random group of points preventing us from making predictions about the value of comments, based on the *social* dimension.

Fig. 20 Impact of *social* on *relative comments* on Twitter

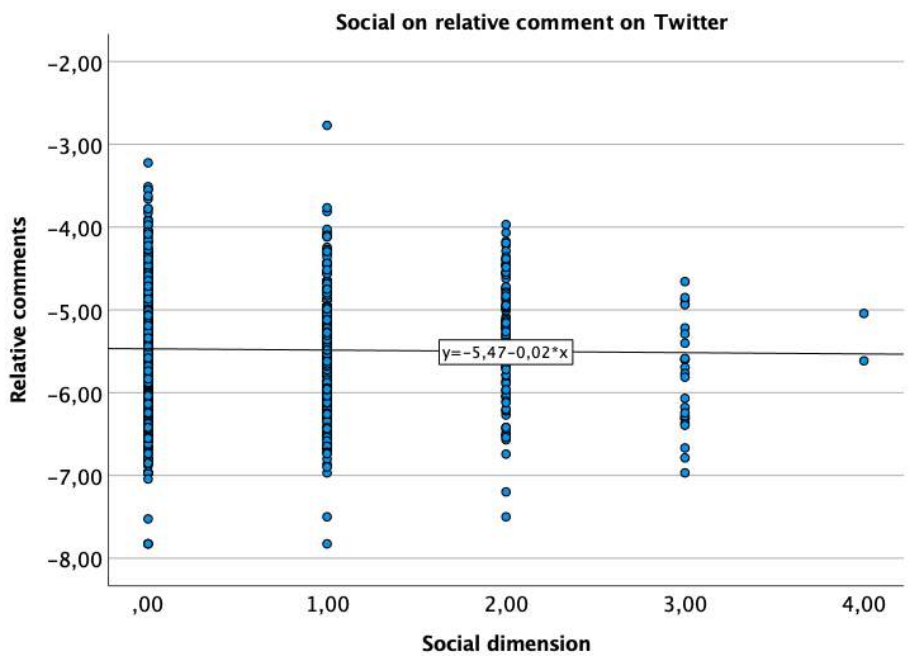
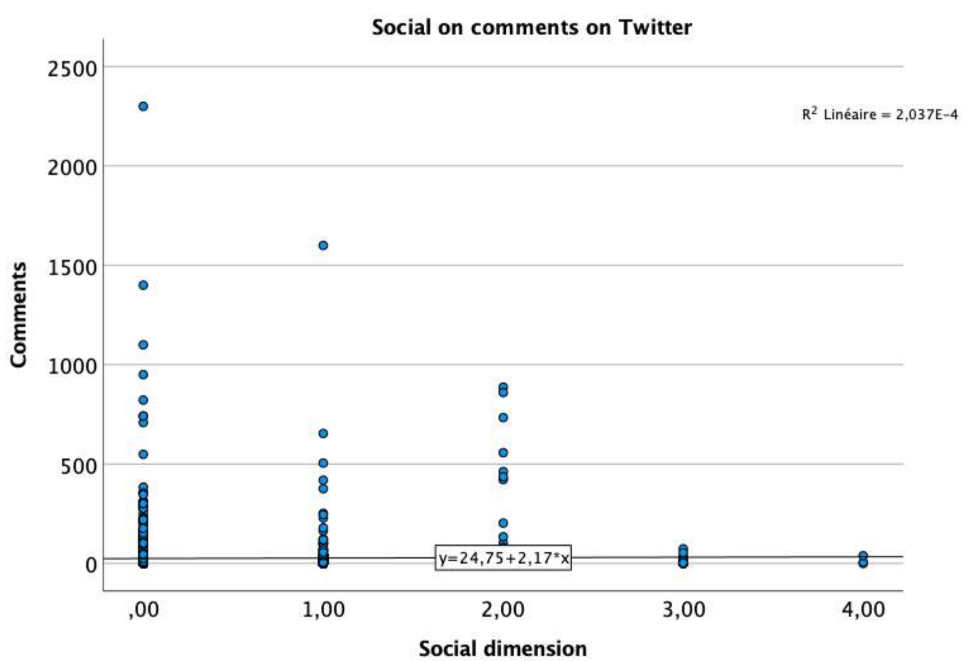


Fig. 21 Impact of *social* on *comments* on Twitter



Content dimensions on Facebook

Table 21 Impact of *content* dimensions on CE on Facebook

	N	*RNG*	*M*	*S.D.*	B	β	*t*	*p*	R^2
Sell. on likes	1,599	5	0.89	1.14	-0.09	-0.17	-7.07	**0.00**	0.19
Sell. on comments	1,599	5	0.89	1.14	-0.09	-0.14	-6.10	**0.00**	0.25
Qual. on likes	1,599	6	1.7	1.11	0.05	0.09	3.57	**0.00**	0.17
Qual. on comments	1,599	6	1.7	1.11	0.01	0.01	0.58	0.56	0.23
Soc. on likes	1,599	4	0.58	0.86	-0.05	-0.08	-3.04	**0.00**	0.17
Soc. on comments	1,599	4	0.58	0.86	-0.06	-0.07	-3.06	**0.00**	0.23

Selling dimension has a decreasing effect on likes and comments as seen on the figures below.

Fig. 22 Impact of *selling* on *relative likes* on Facebook

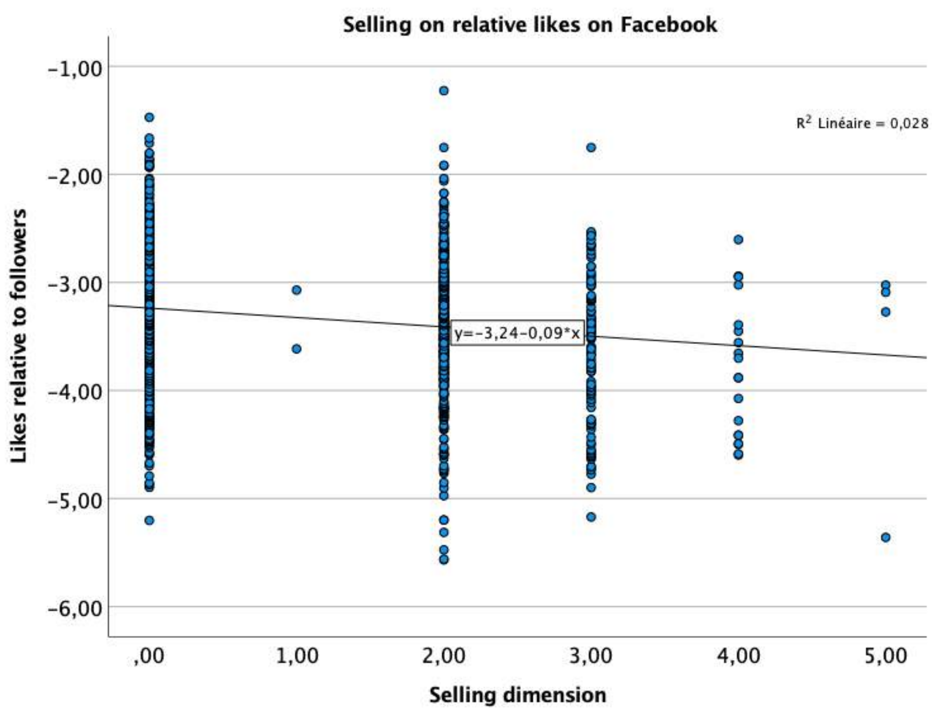


Fig. 23 Impact of *selling* on *likes* on Facebook

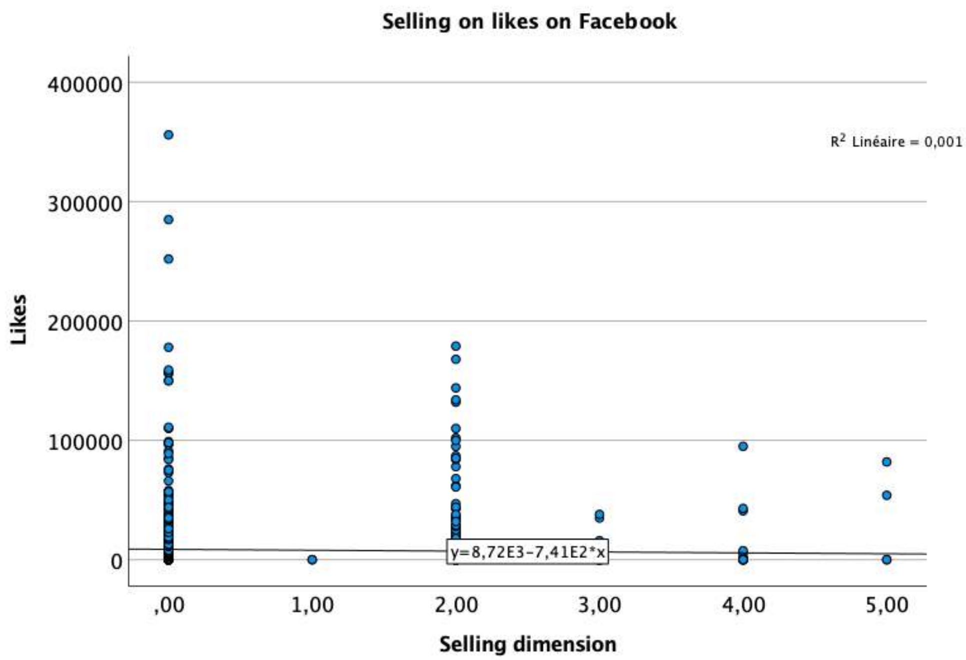


Fig. 24 Impact of *selling* on *relative comments* on Facebook

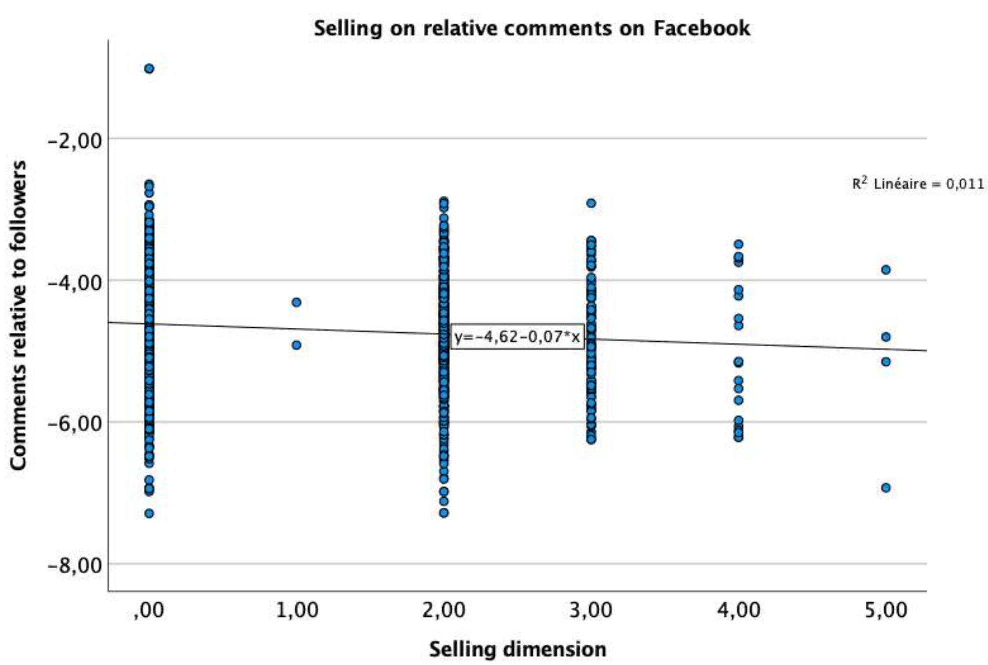
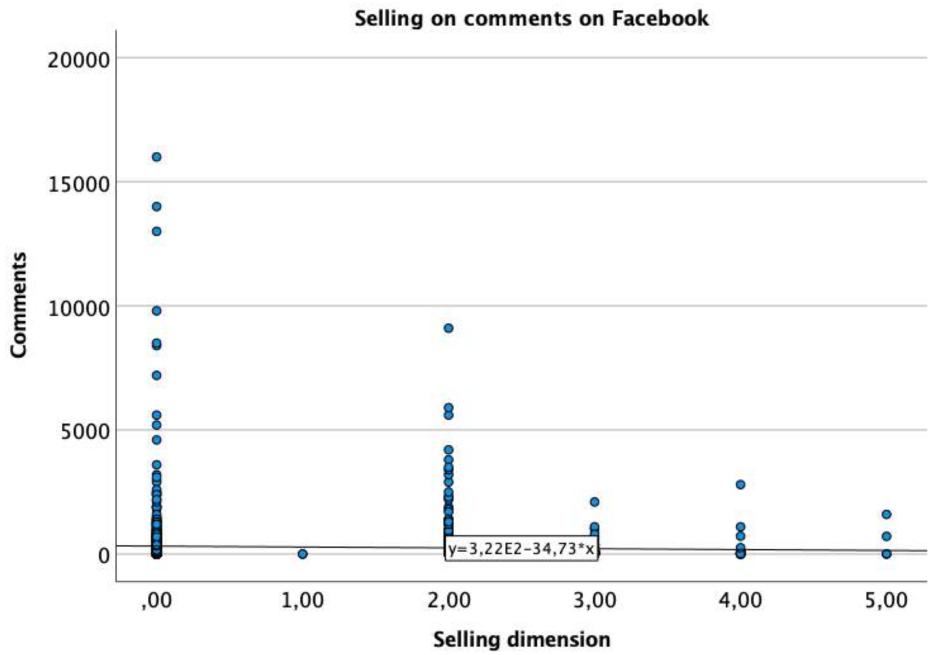


Fig. 25 Impact of *selling* on *comments* on Facebook



Quality increases likes on Facebook. As can be seen below, this increase is subtle.

Fig. 26 Impact of *quality* on *relative likes* on Facebook

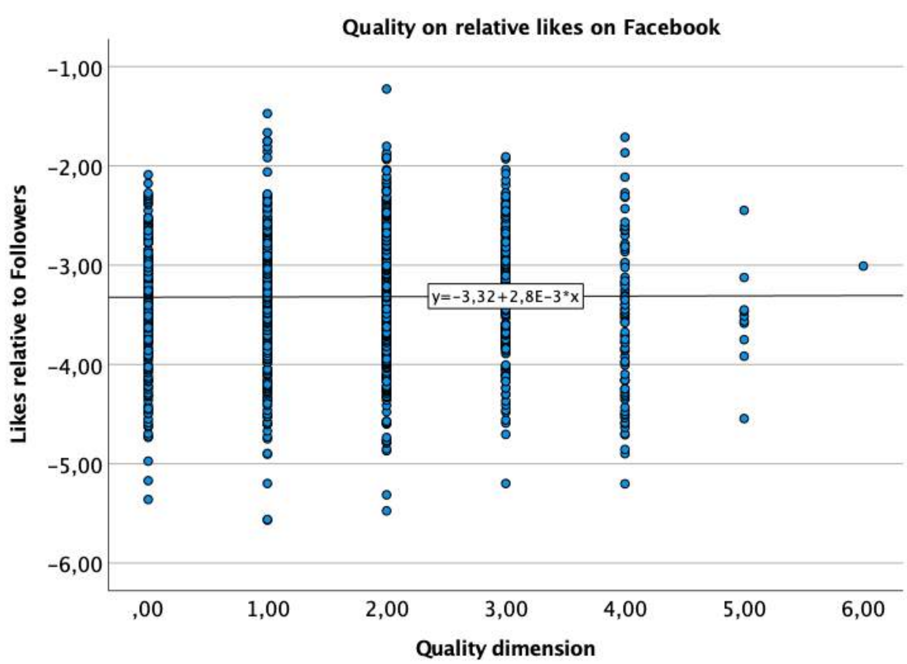
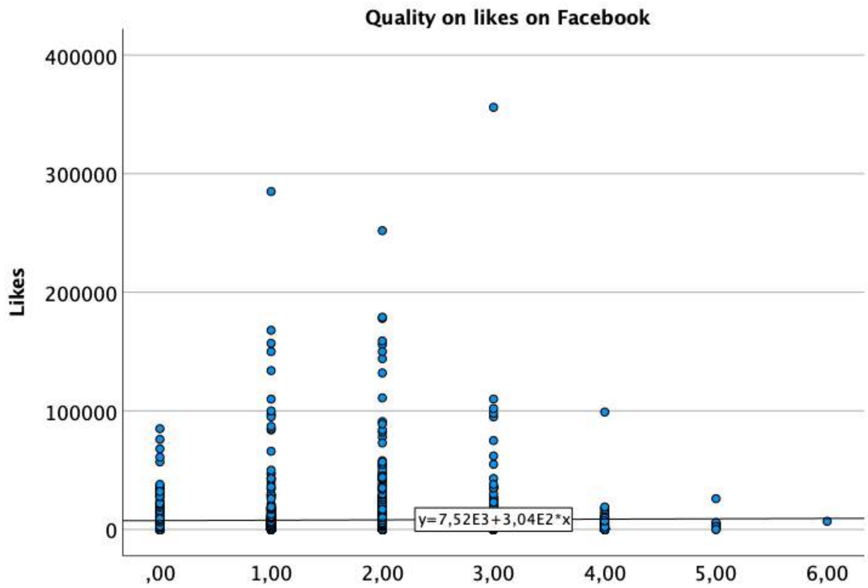


Fig. 27 Impact of *quality* on *likes* on Facebook



As for the *social* dimension on Facebook, unlike the *social* dimension on Twitter, it is also significant on likes. *Social* has a decreasing effect on both likes and comments. Below, the left figures display the variables that have been normalized through a log10 transformation. With normal distributions, the analysis of the results is less ambivalent as illustrated in the figures below.

Fig. 28 Impact of *social* on *relative likes* on Facebook

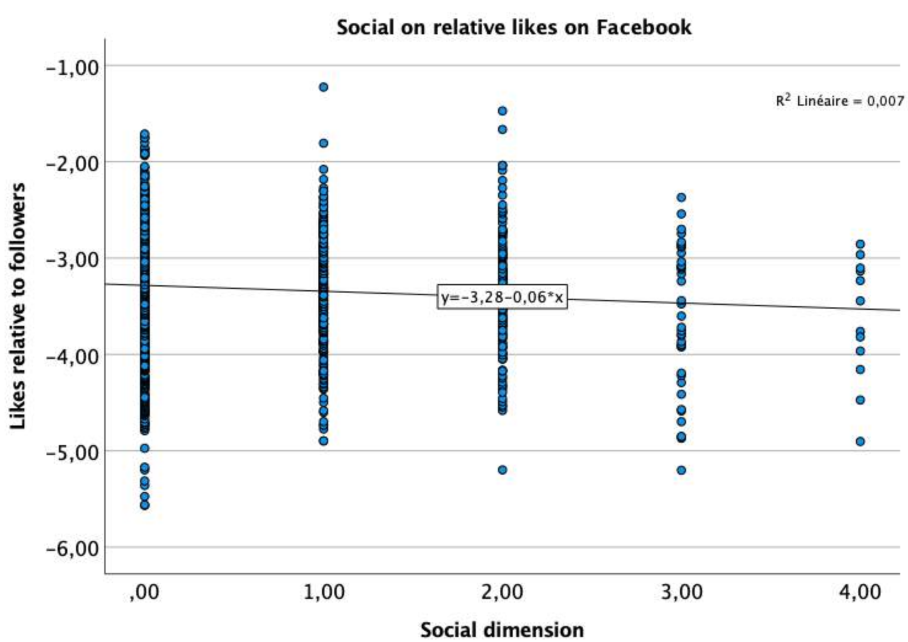


Fig. 29 Impact of *social* on *likes* on Facebook

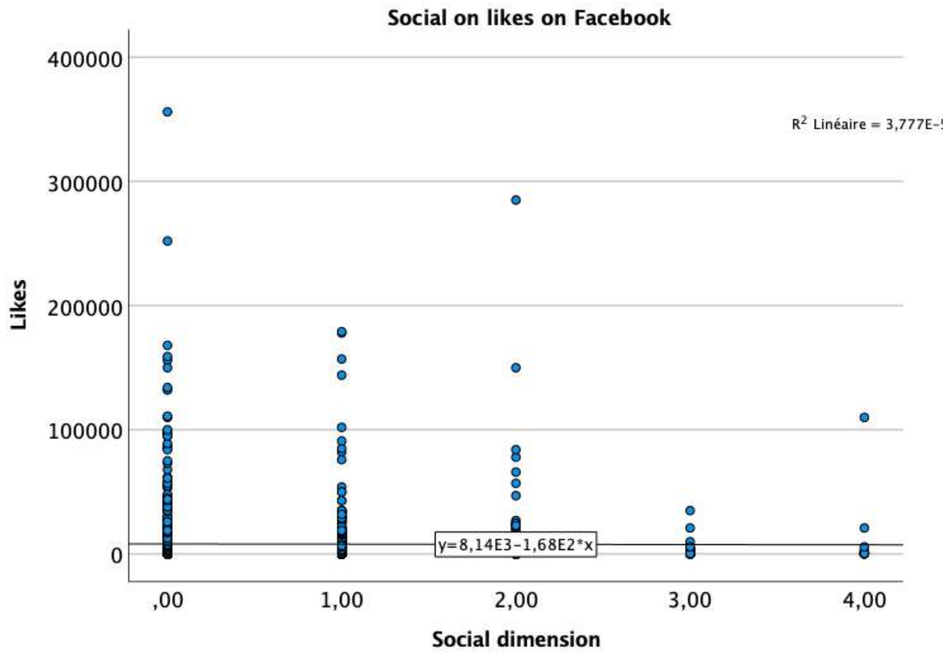


Fig. 30 Impact of *social* on *relative comments* on Facebook

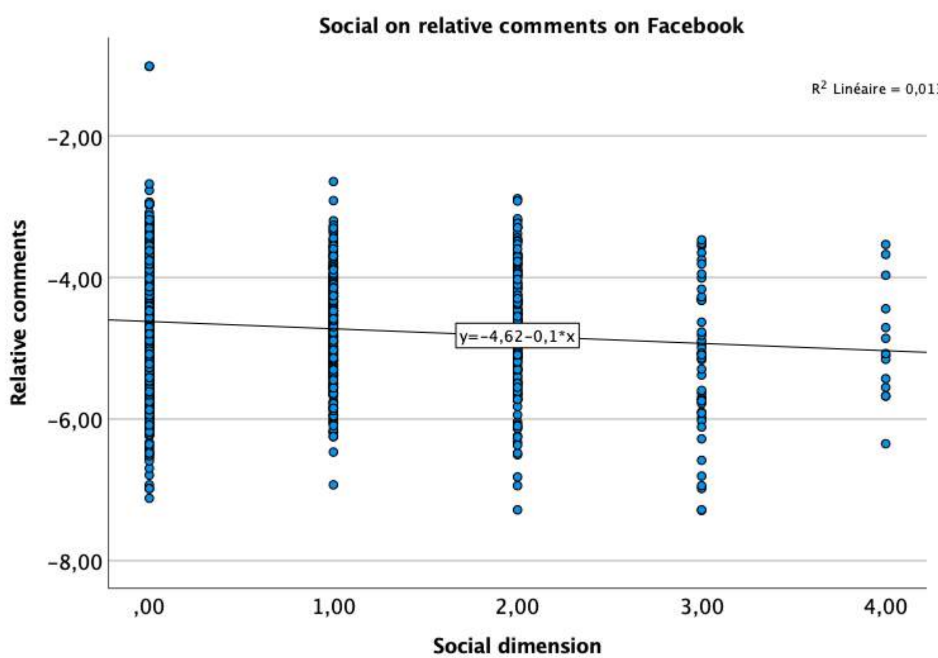
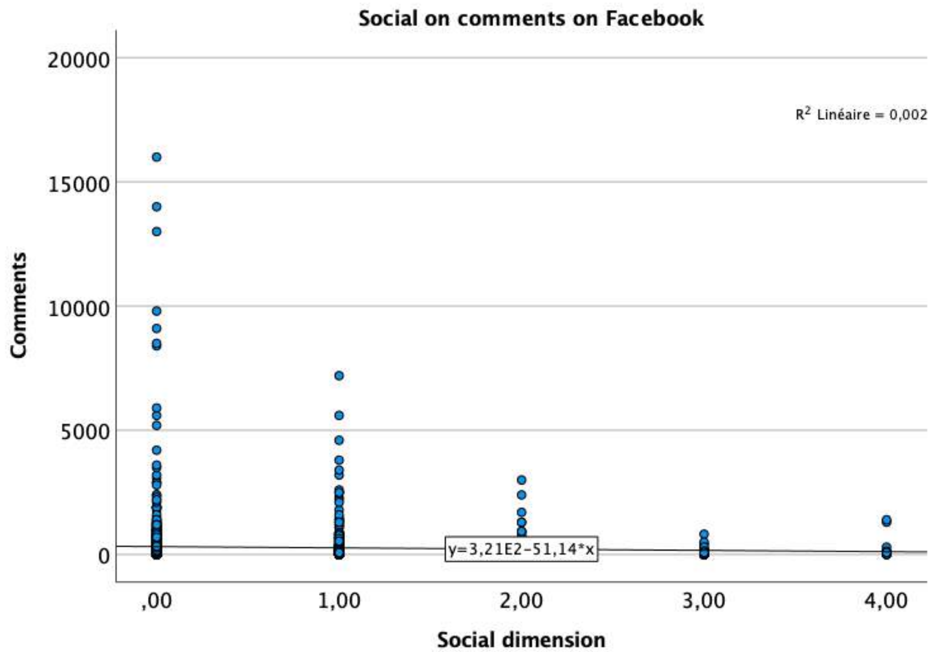


Fig. 31 Impact of *social* on *comments* on Facebook



Content dimensions on Instagram

Table 22 Impact of *content* dimensions on CE on Instagram

Results of Linear Regression Analyses by Content Dimensions on Instagram

	N	*RNG*	*M*	*S.D.*	B	β	*t*	*p*	R^2
Sell. on likes	1,772	4	0.65	1.01	-0.04	-0.10	-4.45	**0.00**	0.26
Sell. on comments	1,772	4	0.65	1.01	-0.03	-0.05	-2.06	**0.04**	0.20
Qual. on likes	1,770	6	1.67	0.96	-0.01	-0.03	-1.42	0.16	0.25
Qual. on comments	1,770	6	1.67	0.96	-0.04	-0.07	-3.11	**0.00**	0.21
Soc. on likes	1,772	4	0.68	0.87	0.01	0.01	0.55	0.58	0.25
Soc. on comments	1,772	4	0.68	0.87	0.04	0.06	1,72	0.08	0.20

Selling dimension has a very slight decreasing effect on likes as seen on the figure below. As for the influence on comments, it is almost nil.

Fig. 32 Impact of *selling* on *relative likes* on Instagram

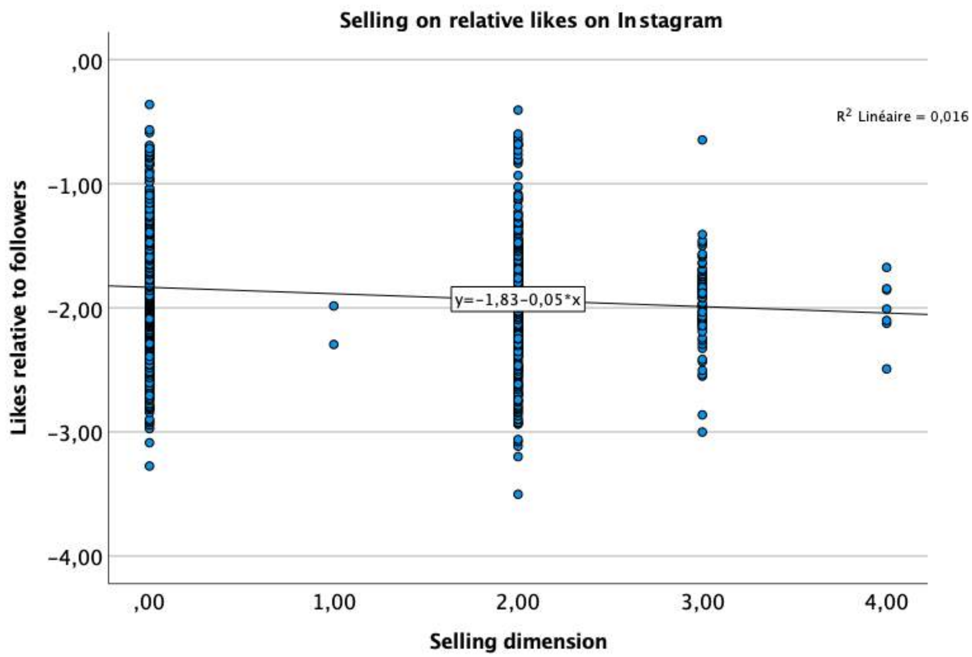


Fig. 33 Impact of *selling* on *likes* on Instagram

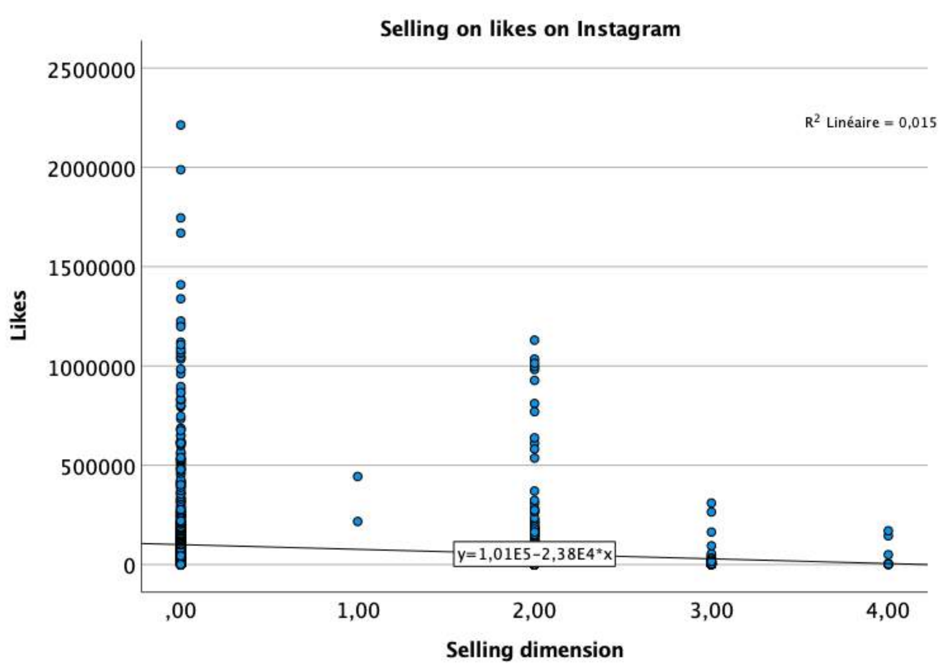


Fig. 34 Impact of *selling* on *relative comments* on Instagram

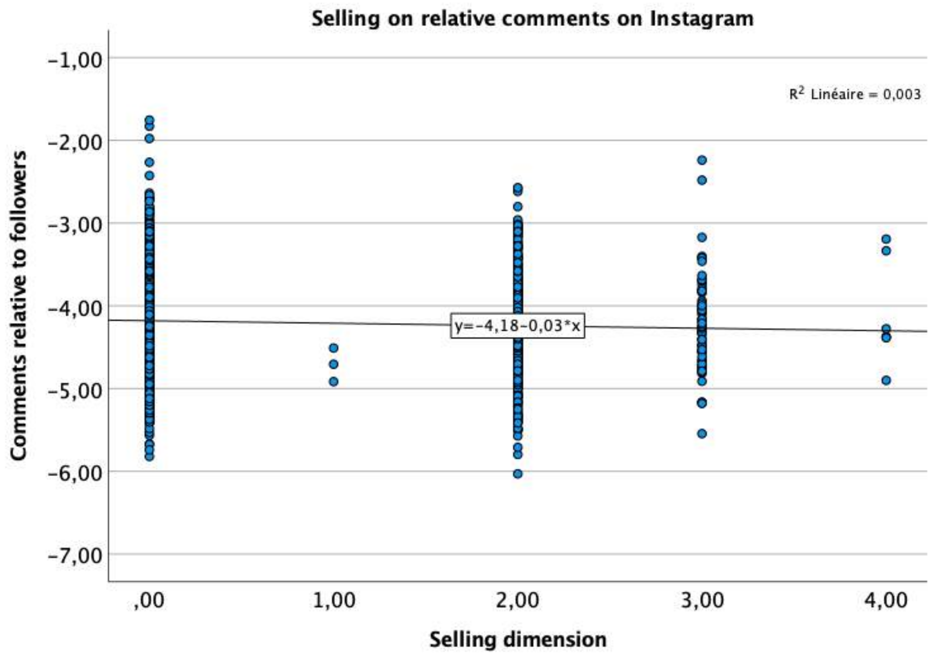
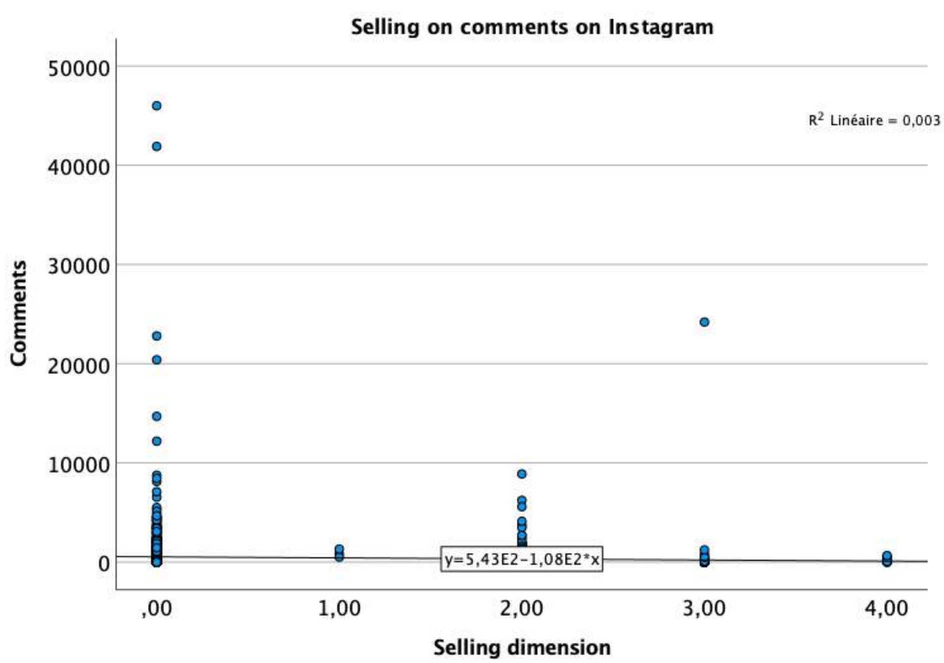


Fig. 35 Impact of *selling* on *comments* on Instagram



Quality has a decreasing effect on comments.

Fig. 36 Impact of *quality* on *relative comments* on Instagram

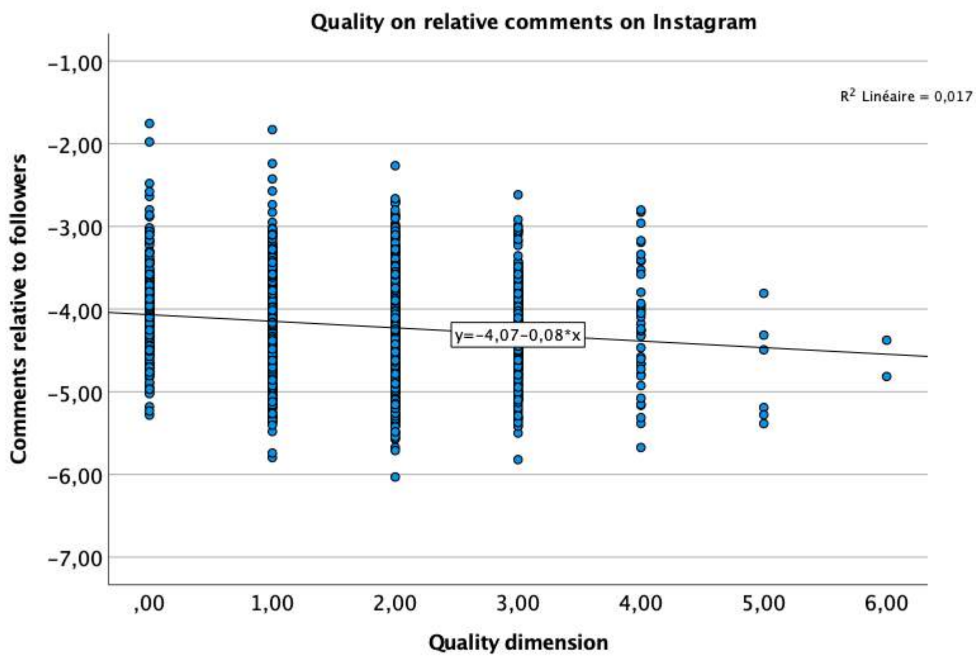
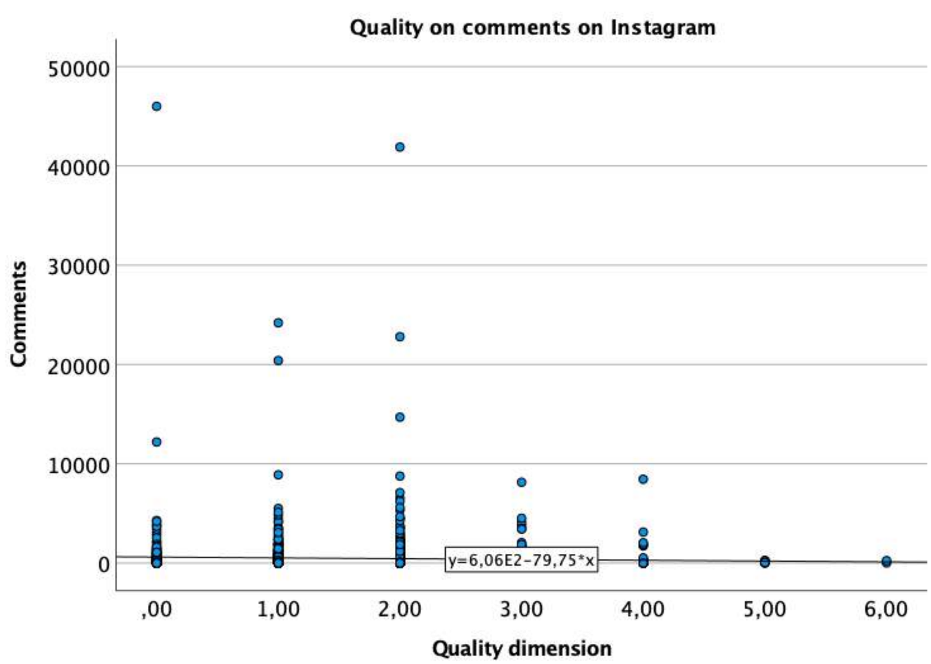


Fig. 37 Impact of *quality* on *comments* on Instagram



Social dimension

Much to our surprise, *social* is not correlated to likes and comments relative to followers on Instagram. This is surprising since Instagram's mission statement revolves around its *social* dimension : "*We bring you* ***closer*** *to the people and things you love*" (Instagram, 2021).

In short, to answer the initial question, **"*to what extent are the different dimensions of content generated by sports organizations associated with consumers' engagement on their official social networking sites* ?"**, results show that the direction and strength of the relationship between content and engagement varies across SNSs.

Selling decreases engagement on all social networks with varying degrees of intensity.
Below, the three-dimensional charts parallel the influence of *selling* on engagement across all social networking sites.
Instagram has the highest engagement rates, while Facebook is in the middle of the spectrum and Twitter shows the lowest initial rates and the steepest decline particularly in likes. It is noteworthy however that only in Twitter do up to seven *selling* subdimensions get used at once on a single post.

Fig. 38 3D graph of *selling* on *relative likes* for all social networking sites

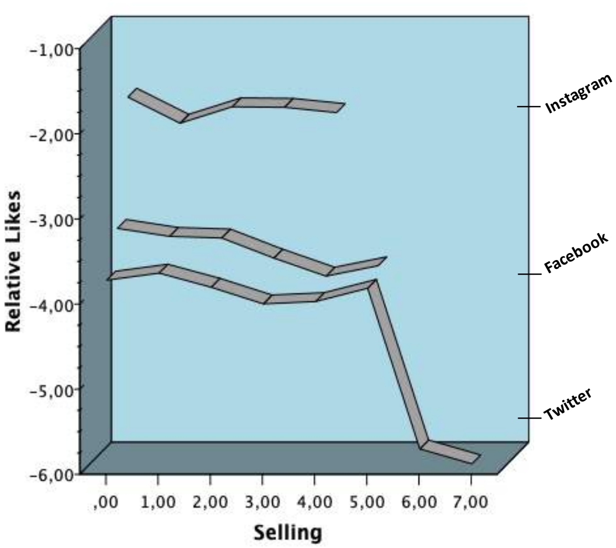
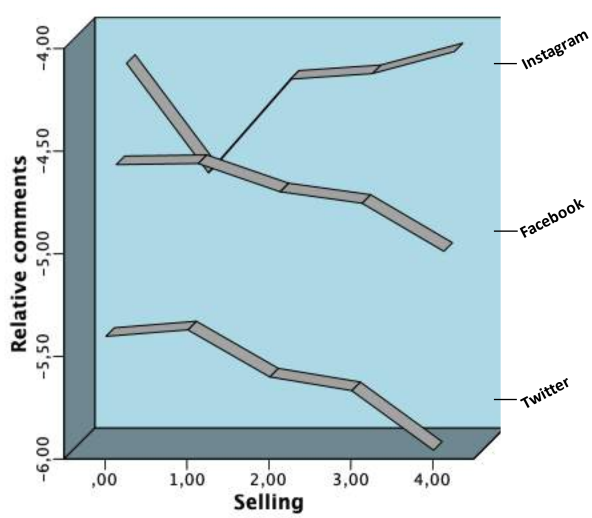


Fig. 39 3D graph of *selling* on *relative comments* for all social networking sites



Quality, on the other hand, has an impact that varies not only in intensity, but also on the direction of the relationship. On Twitter, *quality* increases both *relative likes* and *relative comments*. On the 3D graphs below, the increase of the slope for *relative likes* is more marked than for *relative comments*. On Facebook, generally speaking, *quality* slightly increases *relative likes*. On the 3D graph, we rather observe that when a same publication contains over three *quality* subdimensions, meaning three elements that promote brand quality, *relative likes* decrease and followers disengage. On Instagram, *quality* decreases the number of *relative comments*.

Fig. 40 3D graph of *quality* on *relative likes* for all social networking sites

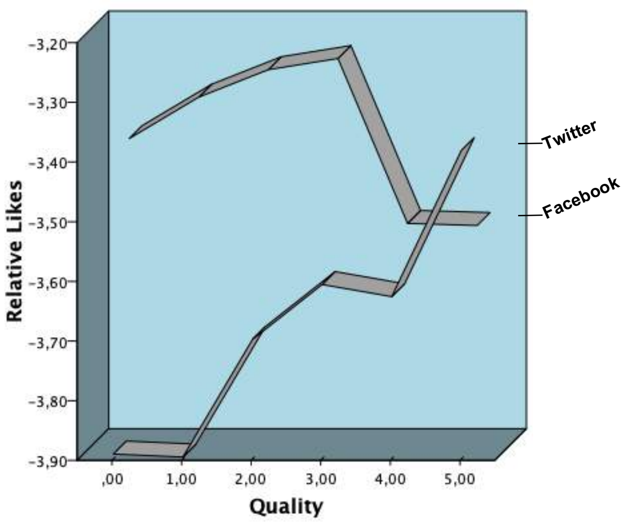
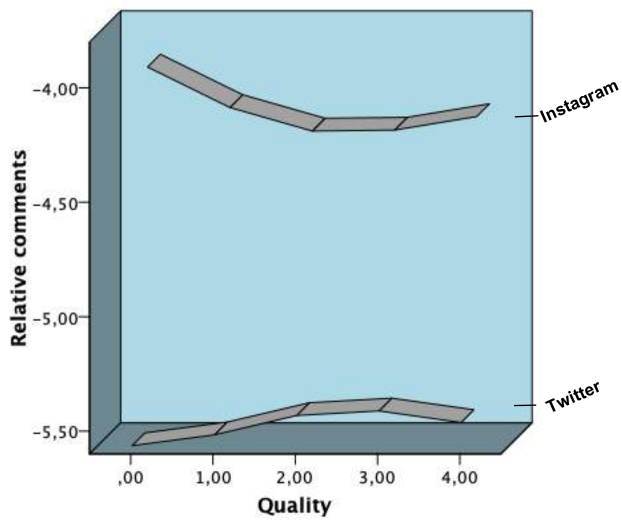


Fig. 41 3D graph of *quality* on *relative likes* for all social networking sites



Like the *quality* dimension, the *social* dimension has an impact that varies in intensity and direction. On Twitter, when averaged over all of the publications analyzed, the *social* dimension boosts comments almost to the zero mark. Nevertheless, in the 3D graph below, we see a more complicated pattern. In the majority of cases, *social* content decreases *relative comments*. Certain combos of *social* content within a single post increase *relative* comments, pushing up the average. This struggle between certain posts increasing *relative comments* and others decreasing them ends with an average impact very close to zero.

Fig. 42 3D graph of *social* on *relative likes* for all social networking sites

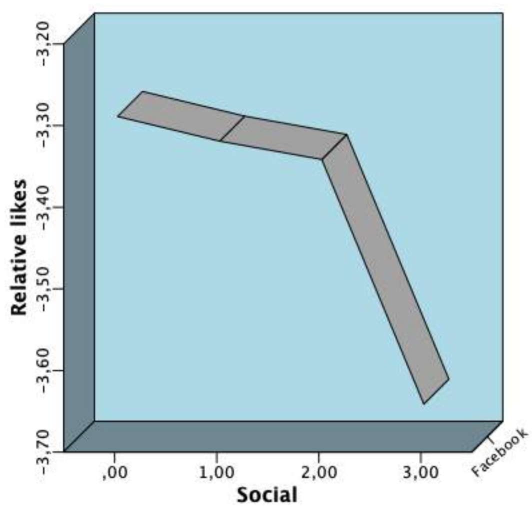
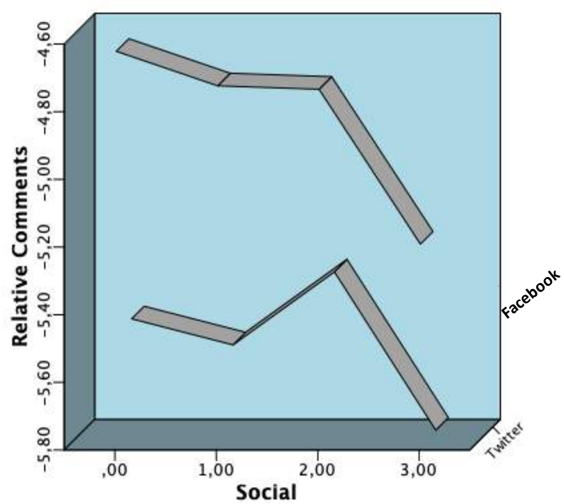


Fig. 43 3D graph of *social* on *relative comments* for all social networking sites



On Facebook, the effect of *social* on engagement is unambiguous. It decreases both *relative likes* and *relative comments*. On Instagram, *social* has no significant influence. Overall, *social* has a zero or negative effect on engagement. Moreover, this is not the result of an overabundance of the *social* dimension since only 36 % of the publications collected on Twitter, 38.5 % on Facebook and 46.7 % on Instagram contain *social*.

4.3.3 Research Question 3

There are significant differences between the 48 sports included in our sample. We hypothesize that ping-pong and extreme sports fans are not engaged by the same types of content. Segmentation between sports is necessary. The *body collision* is a construct close to violence which leads to spectacular plays. Therefore, we ask:**" *How does the risk of body collision in sport impact the relationship between the content dimensions of the FGC and the CE ?"*.**

To answer that third research question, we tested the relationship between each content dimension and each engagement measure, moderated by *body collision,* always keeping our same control variables constant (*Holiday*, *Team/Individual*, *Male*, *Local Association, National Association*, *Privately Owned*, *League* or *Federation*, *National Championship*, *International Championship*, *Continent*, *Vividness*). To do this, we selected one SNS at a time (data select boxes), then processed the 18 logistic regressions with Hayes' PROCESS v 3.5, six per SNS. Then, to better understand the interactions between the variables, via the SPSS syntax function, we created graphs illustrating each significant relationship

($p \leq 0.05$).

<u>On Twitter</u>

As seen below, the average number of *relative likes* and *relative comments* in *collision* sports is higher than those without *collision* (see appendix for).

Table 23 Average number of *relative likes* and *relative comments*

Twitter				
		N	Mean	Std
Likes relative	No collision	603	-3.83	0.74
	Collision	1022	-3.74	0.71
Comments relative	No collision	447	-5.60	0.69
	Collision	692	-5.40	0.70

Table 24 Impact of *content* dimensions moderated by *body collision* on likes on Twitter

	coeff	se	t	p	R^2
Selling dimension on likes					
N : 1617					
M : bodycoll	-0.05	0.05	-0.91	0.36	
Int_1	0.09	0.03	3.26	**0.00**	0.23
Quality dimension on likes					
N : 1616					
M : bodycoll	-0.05	0.08	-0.71	0.48	
Int_1	0.06	0.03	1.64	0.10	0.2
Social dimension on likes					
N : 1617					
M : bodycoll	0.00	0.05	-0.02	0.98	
Int_1	0.10	0.05	2.12	**0.03**	0.19

Table 25 Impact of *content* dimensions moderated by *body collision* on *comments* on Twitter

	coeff	se	t	p	R^2
Selling dimension on comments					
N : 1133					
M : bodycoll	0.37	0.06	6.00	**0.00**	
Int_1	0.04	0.04	1.08	0.28	0.17
Quality dimension on comments					
N : 1133					
M : bodycoll	0.42	0.09	4.70	**0.00**	
Int_1	0.00	0.04	0.13	0.89	0.14
Social dimension on comments					
N : 1133					
M : bodycoll	0.42	0.06	6.92	**0.00**	
Int_1	0.01	0.05	0.17	0.87	0.14

On Twitter, the moderating effect of *body collision* on the relationship between the type of content and engagement performances is significant in two cases. First, looking at the *selling* dimension, sports without *collision* have higher initial engagement rates, measured in relative likes. However, as the *selling* dimension increases, the number of *relative likes* decrease at a faster pace than *collision* sports, which have a better tolerance for *selling* content.

Fig. 44 Impact of *selling* on *relative likes* moderated by *body collision* on Twitter

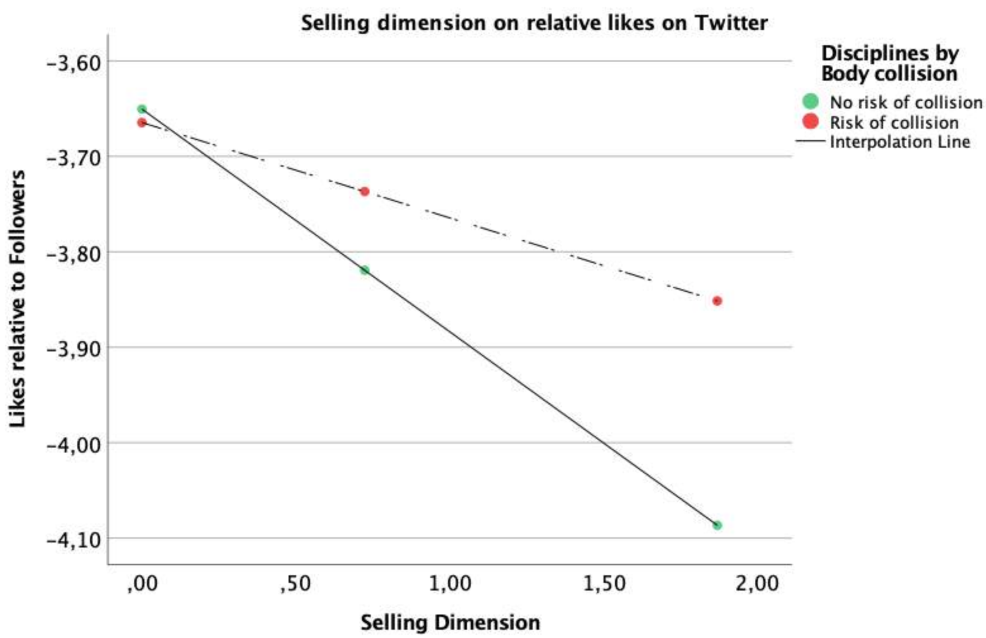
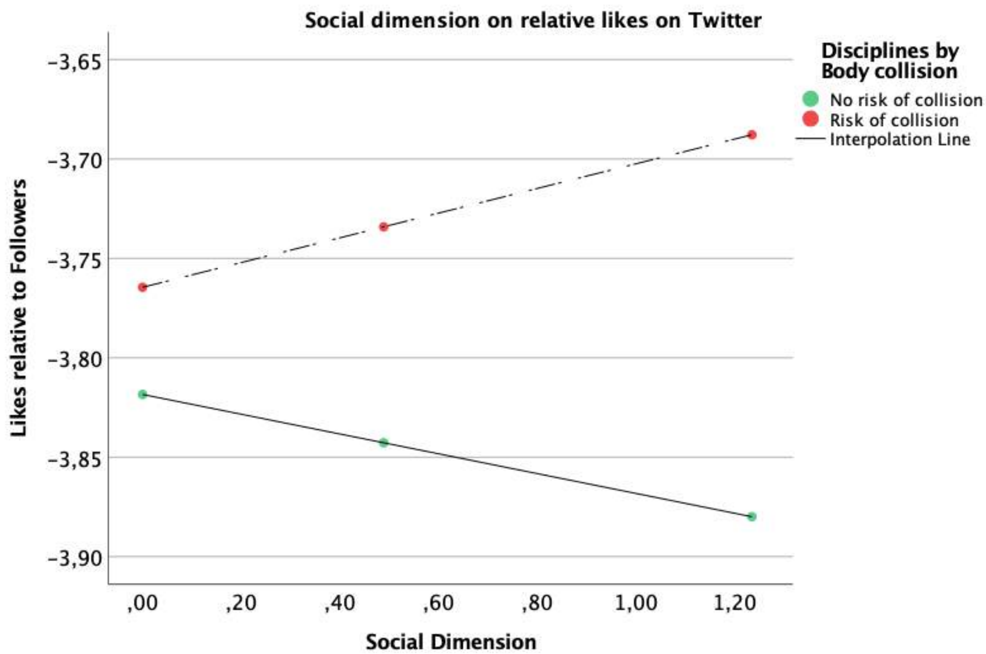


Fig. 45 Impact of *social* on *relative likes* moderated by *body collision* on Twitter



The moderating effect of *body collision* is also significant on the relationship between the *social* dimension and the number of *relative likes*. The more the *social* dimension increases, the more the gap widens between the engagement quantified in *relative likes* in sports with *collision* and sports without *collision*. The two curves evolve in diametrically opposite ways. In *collision* sports, posting *social* increases the number of *relative likes*, whereas in non-*collision* sports it decreases the number of *relative likes*.

On Facebook

Again, on Facebook, the overall average number of *relative likes* and *relative comments* in *collision* sports is higher than those without *collision*.

Table 26 Average number of *relative likes* and *relative comments* on Facebook

Facebook		N	Mean	Std
Likes relative	No collision	634	-3.36	0.62
	Collision	815	-3.28	0.58
Comments relative	No collision	682	-4.82	0.79
	Collision	864	-4.57	0.75

Table 27 Impact of *content* dimensions moderated by *body collision* on *likes* on Facebook

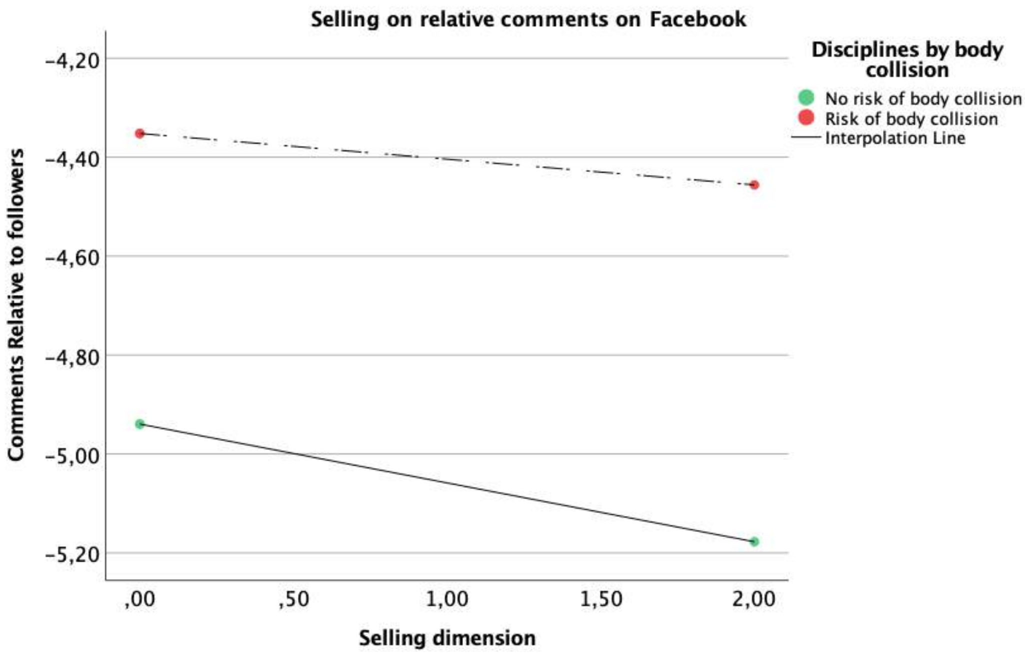
	coeff	se	t	p	R^2
Selling dimension on likes					
N : 1449					
M : bodycoll	0.24	0.04	5.30	**0.00**	
Int_1	0.04	0.03	1.62	0.11	0.18
Quality dimension on likes					
N : 1449					
M : bodycoll	0.36	0.06	5.86	**0.00**	
Int_1	-0.05	0.03	-1.72	0.08	0.16
Social dimension on likes					
N : 1449					
M : bodycoll	0.25	0.04	5.87	**0.00**	
Int_1	0.04	0.03	1.11	0.27	0.16

Table 28 Impact of *content* dimensions moderated by *body collision* on *comments* on Facebook

		coeff	se	t	p	R^2
Selling dimension on comments						
	N : 1546					
	M : bodycoll	0.59	0.06	10.59	**0.00**	
	Int_1	0.07	0.03	2.08	**0.04**	0.22
Quality dimension on comments						
	N : 1546					
	M : bodycoll	0.87	0.08	11.62	**0.00**	
	Int_1	-0.13	0.03	-3.92	**0.00**	0.21
Social dimension on comments						
	N : 1546					
	M : bodycoll	0.64	0.05	12.28	**0.00**	
	Int_1	0.01	0.04	0.18	0.86	0.21

On Facebook, *body collision* also moderates the relationship between the type of content and engagement performances in two cases. First, content with a *selling* dimension decreases the number of comments for sports with or without collision. However, the figure below illustrates a greater tolerance for *selling* dimension among followers of *collision* sports than among followers of non-collision sports. Indeed, in sports without collision, the slope is a little steeper, as the more the *selling* increases, the more the likes decrease quickly.

Fig. 46 Impact of *selling* on *relative comments* moderated by *body collision* on Facebook



As for the dimension of *quality* and its influence on the *relative comments*, the two categories of followers have opposite reactions. In *collision* sports, as the *quality* dimension increases, *relative comments* decrease. For sports without collision, *relative comments* increase steadily in sync with *quality* content.

Fig. 47 Impact of *quality* on *relative comments* moderated by *body collision* on Facebook

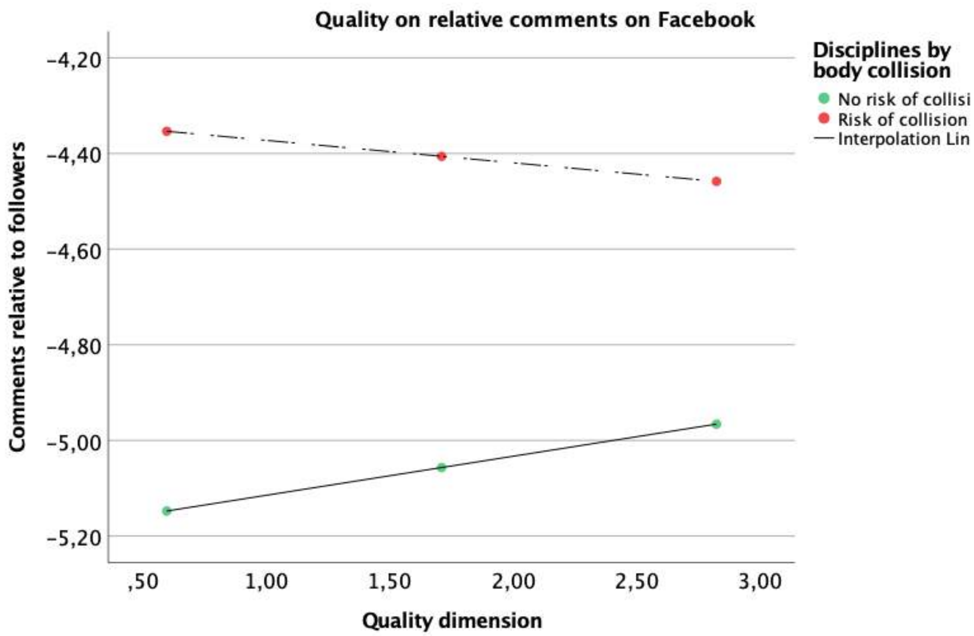
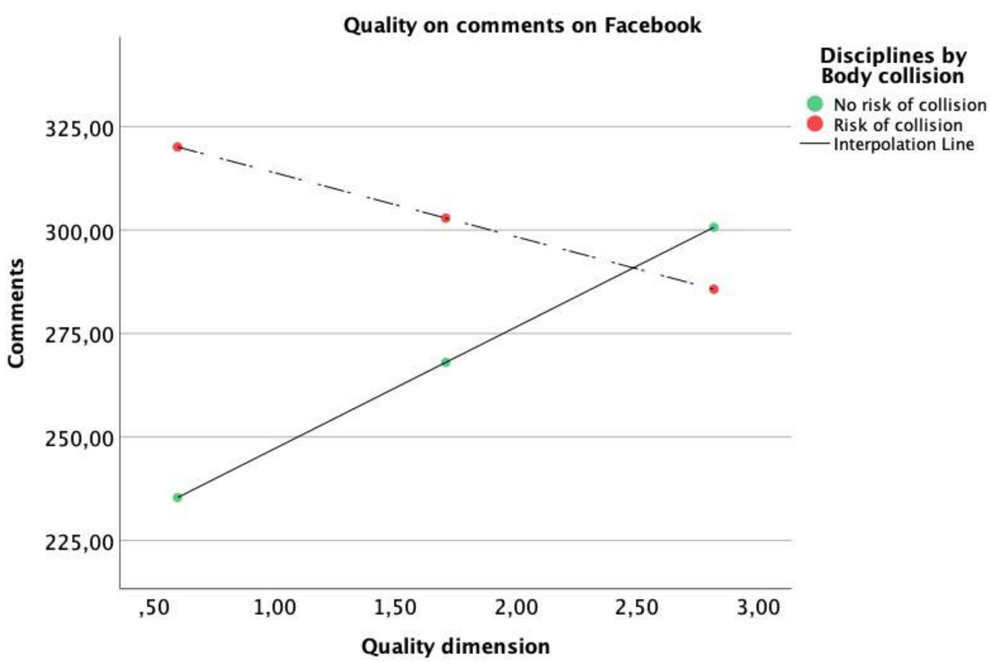


Fig. 48 Impact of *quality* on absolute *comments* moderated by *body collision* on Facebook



On Instagram

On Instagram, just like on Twitter and Facebook, the average numbers of *relative likes* and *relative comments* in *collision* sports are higher than those without collision.

Table 29 Average number of *relative likes* and *relative comments* on Instagram

Instagram				
		N	Mean	Std
Likes relative	No collision	673	-1.88	0.48
	Collision	1076	-1.86	0.38
Comments relative	No collision	659	-4.26	0.66
	Collision	1085	-4.16	0.55

Table 30 Impact of *content* dimensions on *likes* moderated by *body collision* on Instagram

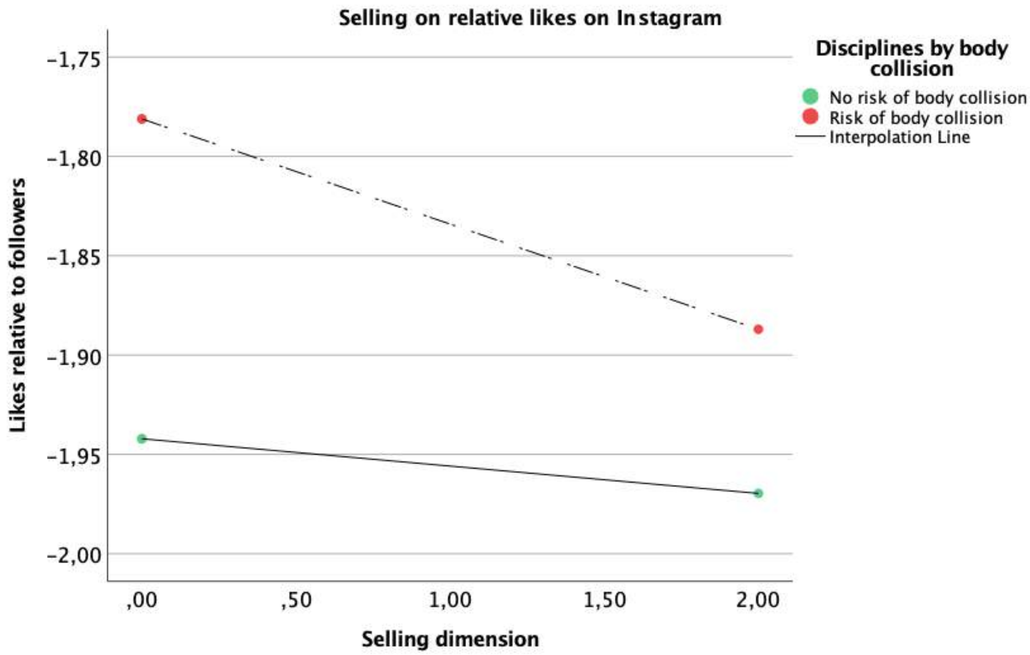
	coeff	se	t	p	R^2
Selling dimension on likes					
N: 1742					
M : bodycoll	0.16	0.03	5.97	**0.00**	
Int_1	-0.04	0.02	-2.04	**0.04**	0.22
Quality dimension on likes					
N : 1745					
M : bodycoll	0.19	0.04	4.58	**0.00**	
Int_1	-0.03	0.02	-1.47	0.14	0.22
Social dimension on likes					
N : 1747					
M : bodycoll	0.15	0.03	5.51	**0.00**	
Int_1	-0.02	0.02	-1.12	0.26	0.22

Table 31 Impact of *content* dimensions on *comments* moderated by *body collision* on Instagram

		coeff	se	t	p	R^2
Selling dimension on comments						
	N : 1742					
	M : bodycoll	0.29	0.04	7.28	**0.00**	
	Int_1	-0.04	0.03	-1.50	0.13	0.17
Quality dimension on comments						
	N : 1740					
	M : bodycoll	0.32	0.06	5.38	**0.00**	
	Int_1	-0.03	0.03	-1.18	0.24	0.17
Social dimension on comments						
	N : 1742					
	M : bodycoll	0.30	0.04	7.50	**0.00**	
	Int_1	-0.07	-0.07	-2.20	**0.03**	0.17

The tendency observed below is the reverse of that observed on Twitter and Facebook. In this case, *collision* sports followers have less tolerance to *selling* (in likes). Although they have a higher initial level of likes, the decrease in the number of likes in response to *selling* content is steeper than for non-collision sports.

Fig. 49 Impact of *selling* on *relative likes* moderated by *body collision* on Instagram



Posting *social* content increases the number of comments irrespective of the risk of *body collision*.

Fig. 50 Impact of *social* on *relative comments* moderated by *body collision* on Instagram

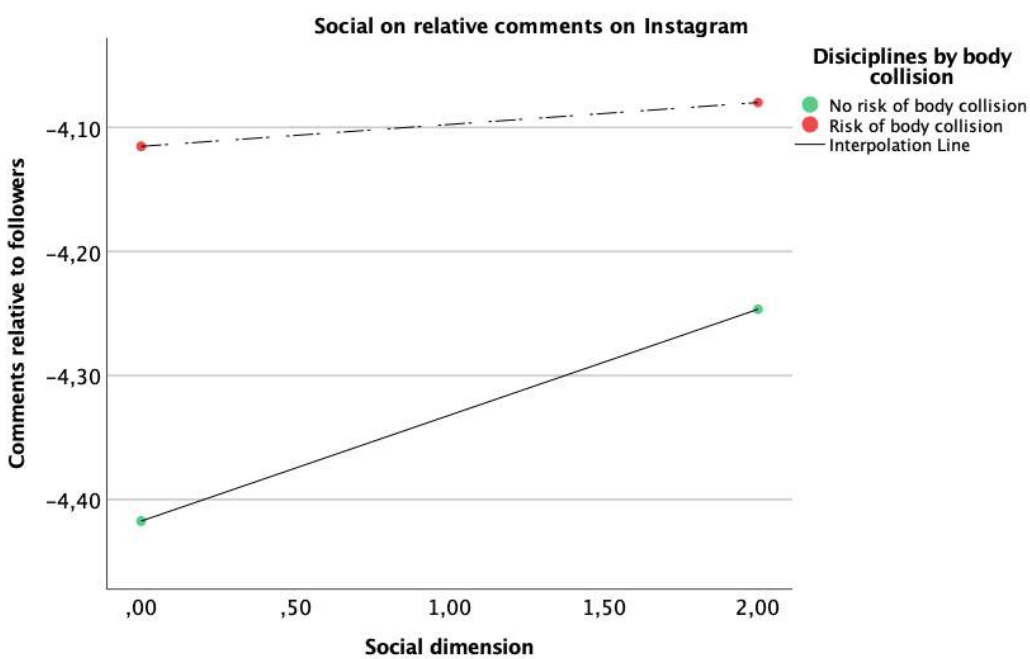


Fig. 51 Impact of *social* on *absolute comments* moderated by *body collision* on Instagram

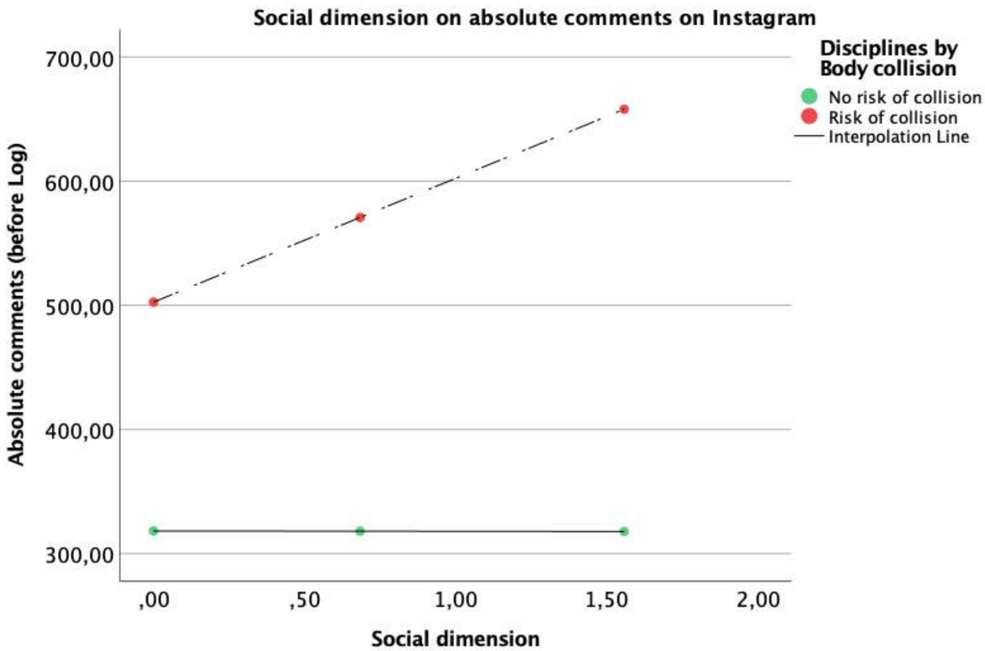
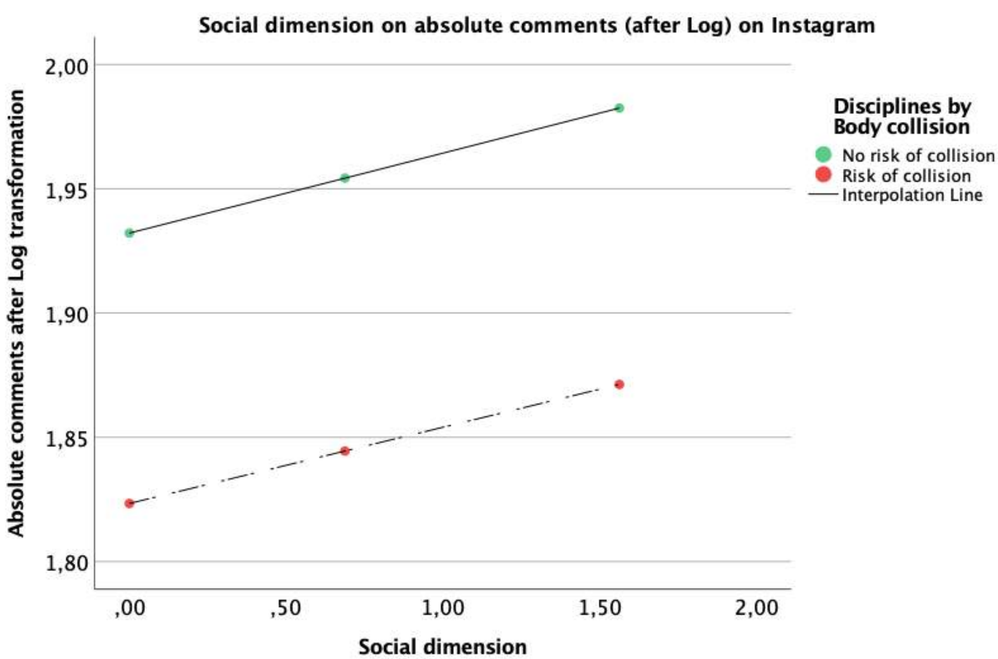


Fig. 52 Impact of *social* on *absolute comments* after Log10 moderated by *body collision* on Instagram



In short, to answer question 3 namely, "***How does the risk of body collision in sport impact the relationship between the content dimensions of the FGC and the CE ?***".

The risk of *collision* in sports affects the relationship between the content published by sports organizations and the engagement it generates. Posts from *collision* disciplines garner on average 25 % more likes and comments per post than those from non-collision sports.

On Twitter and Facebook, fans of *collision* sports have a higher tolerance for *selling*, than do fans of non-collision sports. On Twitter, although results obtained in question 2 indicated that *social* had little to no effect on likes, for collision sports followers, this content type spikes the number of likes. This effect was offset by the fact that, conversely, *social* decreases likes among non-collision sports followers.

A similar phenomenon is seen with *quality* on Facebook. While our previous results indicated that the dimension had no influence on comments, it would appear that two opposing trends are cancelling each other out : *quality* decreases comments in *collision sports* but increases them in non-collision sports.

On Instagram, all categories respond well to *social*. As *social* increases, so do the comments. The discrepancies in the regression curves mirror the range in engagement that different types of *social* content elicit among non-collision sports followers. The Log transformation flattened those variation peaks out of the standard curve and made it easier to see the average upward trend.

4.3.4 Research Question 4

As the formative model was chosen, the subdimensions could be completely uncorrelated. We wonder, does the analysis of the subdimensions give us a more precise portrait of user preferences ?

> ***To what extent are the different subdimensions of content generated by sports organizations associated with consumers' engagement on their official SNS ? How does the risk of body collision in sport impact the relationship between the content subdimensions of the FGC and the CE ?***

To answer that fourth research question, the first step was sorting cases by SNS (Twitter / Facebook / Instagram). Then, each subdimension was treated as an independent variable predicting engagement, either measured in likes relative to the number of followers or comments relative to the number of followers. Haynes' v3.5 Process Macro was then used to measure whether the risk of *collision* in sports changes the direction or strength of the relationship between each subdimension of content and our two measures of user online engagement. The same control variables were kept constant (*Holiday*, *Team/Individual*, *Male*, *Local Association*, *National Association*, *Privately Owned*, *League or Federation*, *National Championship*, *International Championship*, *Continent*, *Vividness*).

A total of 180 separate regressions were performed (or 60/platform (SNS)). Figures were then produced to better visualize the interactions between the variables. Only those with a significant moderator ($p \leq 0.05$) appear in the paper. Only when the interpretation of the figures is confusing, a second figure is made with the original data (in absolute numbers), before the conversion into relative to followers' numbers and the Log10 transformation. The increase in the variance thus facilitates the interpretation of the data.

Table 32 *Selling* subdimensions on *likes* on Twitter

Even at the subdimension level, *selling* decreases engagement.

Selling subdimensions	β	se	*t*	*p*	R^2
Explicit selling	-0.57	0.12	-4.59	**0.00**	
bodycoll*Explicit	0.14	0.16	0.88	0.38	0.2
Implicit selling	-0.22	0.04	-5.64	**0.00**	
bodycoll*Implicit	0.25	0.07	3.65	**0.00**	0.21
Product	-0.36	0.09	-3.96	**0.00**	
bodycoll*Product	-0.33	0.11	-3.06	**0.00**	0.19
Price	-0.32	0.33	-0.96	0.34	
bodycoll*Price	-0.06	0.46	-0.14	0.89	0.18
Subscrip	-0.47	0.18	-2.59	**0.01**	
bodycoll*Suscrip	-0.47	0.27	-1.75	0.08	0.19
EventMarketing	-0.28	0.17	-1.71	0.09	
bodycoll*EventM	0.05	0.22	0.24	0.81	0.18
EventsTickets	-0.15	0.05	-3.29	**0.00**	
bodycoll*EventT	-0.06	0.06	-0.92	0.36	0.18
PrizeDraws	-0.60	0.11	-5.63	**0.00**	
bodycoll*PrizeDraws	-0.49	0.13	-3.84	**0.00**	0.19
CrossPromo	-0.40	0.05	-8.65	**0.00**	
bodycoll * Cross	-0.18	0.07	-2.84	**0.00**	0.19
Mean	-3.77				
Standard Deviation	0.72				
N	1,617				

Table 33 *Selling* subdimensions on *comments* on Twitter

Selling subdimensions	β	se	*t*	*p*	R^2
Explicit selling	-0.26	0.11	-2.43	**0.02**	
bodycoll*Explicit	-0.06	0.15	-0.40	0.69	0.1
Implicit selling	-0.27	0.05	-5.85	**0.00**	
bodycoll*Implicit	0.55	0.08	6.75	**0.00**	0.16
Product	-0.37	0.13	-2.95	**0.00**	
bodycoll*Product	-0.26	0.15	-1.72	0.09	0.1
Price	-0.13	0.39	-0.33	0.74	
bodycoll*Price	-0.09	0.67	-0.14	0.89	0.1
Subscrip	-0.60	0.25	-2.38	**0.02**	
bodycoll*Suscrip	0.56	0.67	0.83	0.41	0.1
EventMarketing	0.10	0.23	0.44	0.66	
bodycoll*EventM	0.30	0.28	1.09	0.28	0.1
EventsTickets	-0.13	0.06	-2.34	**0.02**	
bodycoll*EventT	0.15	0.08	1.89	0.06	0.1
PrizeDraws	-0.52	0.14	-3.81	**0.00**	
bodycoll*PrizeDraws	-0.28	0.18	-1.59	0.11	0.1
CrossPromo	-0.37	0.06	-6.68	**0.00**	
bodycoll * Cross	-0.18	0.08	-2.29	**0.02**	0.21
Mean	-5.48				
Standard Deviation	0.70				
N	1,133				

Across Twitter, for those relationships that are significant, the risk of *collision* eases the downward slope between the *selling* subdimensions and user engagement online. Thus, *collision* sports followers have a higher tolerance for *Implicit Selling* (in likes and comments), *Product Promotion* (in likes), *Prize Draws* (in likes) and *Cross-Promotions* than non-collision sports followers (in likes and comments).

Fig. 53 Impact of *Implicit Selling* on *relative likes* on Twitter

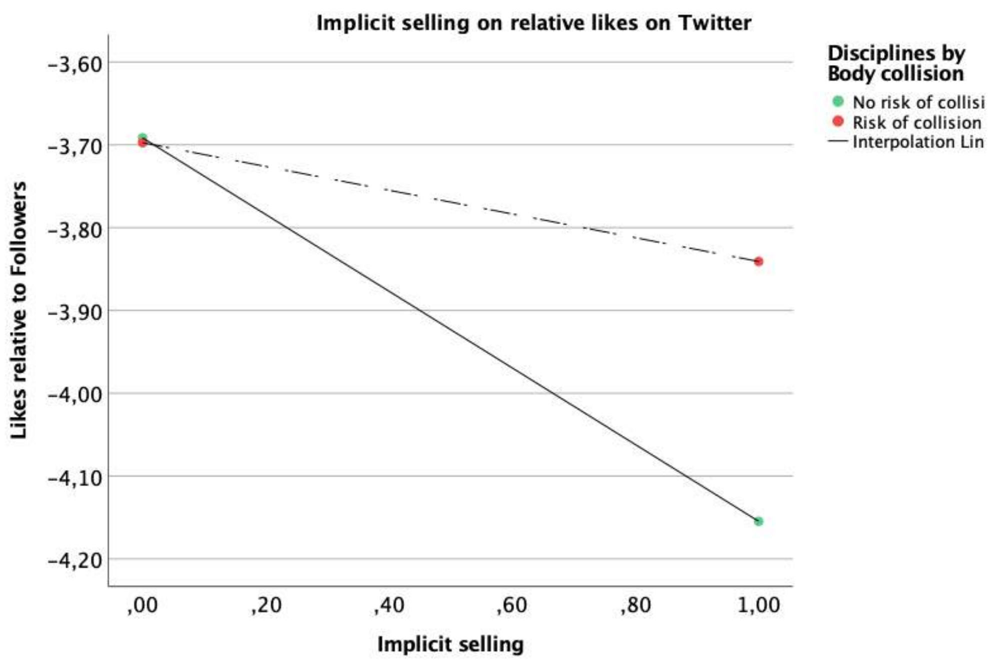


Fig. 54 Impact of *Implicit Selling* on *relative comments* on Twitter

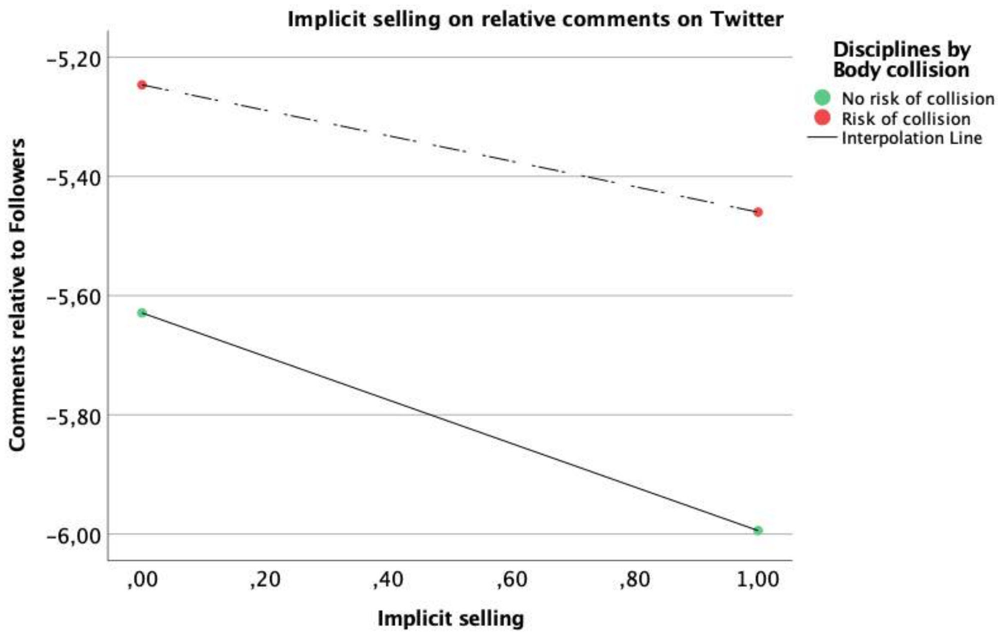


Fig. 55 Impact of *Product/Family* on *likes* on Twitter

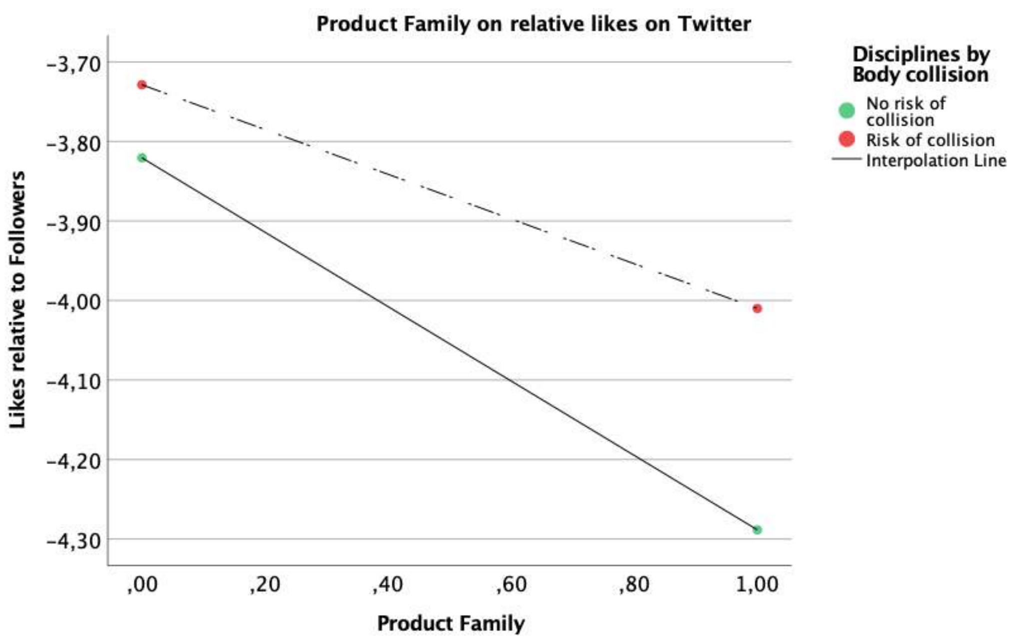


Fig. 56 Impact of *Prize Draws* on *likes* on Twitter

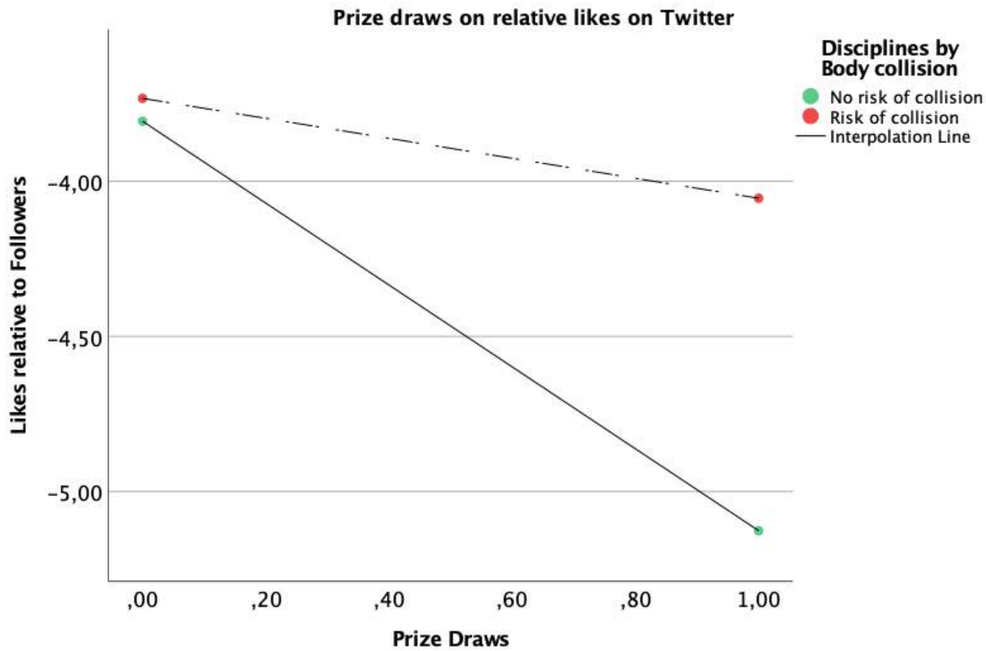


Fig. 57 Impact of *Cross-Promotion* on *relative likes* on Twitter

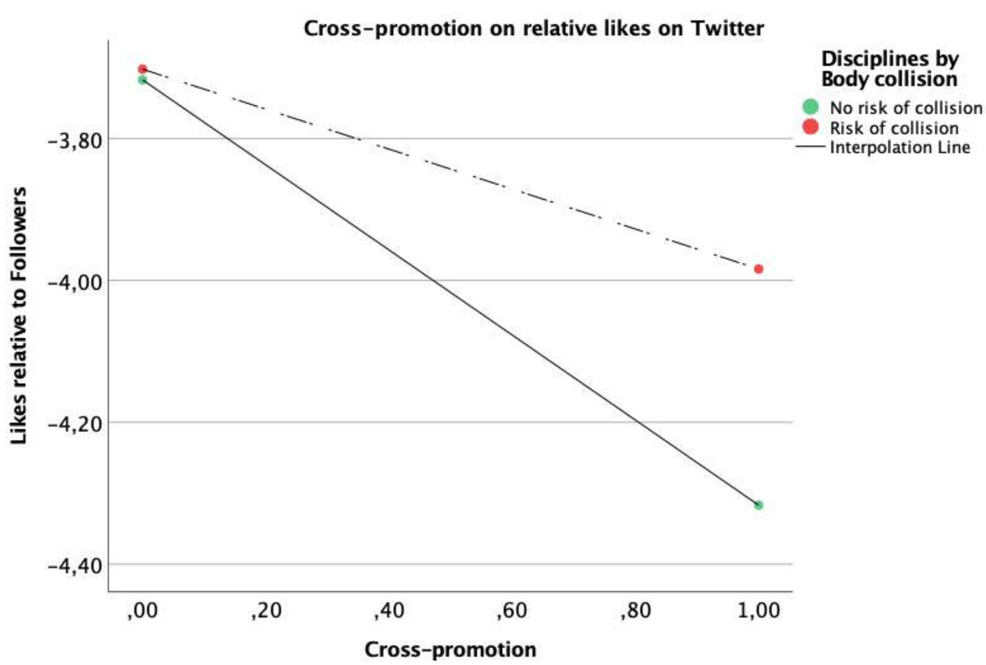


Fig. 58 Impact of *Cross-Promotion* on *relative comments* on Twitter

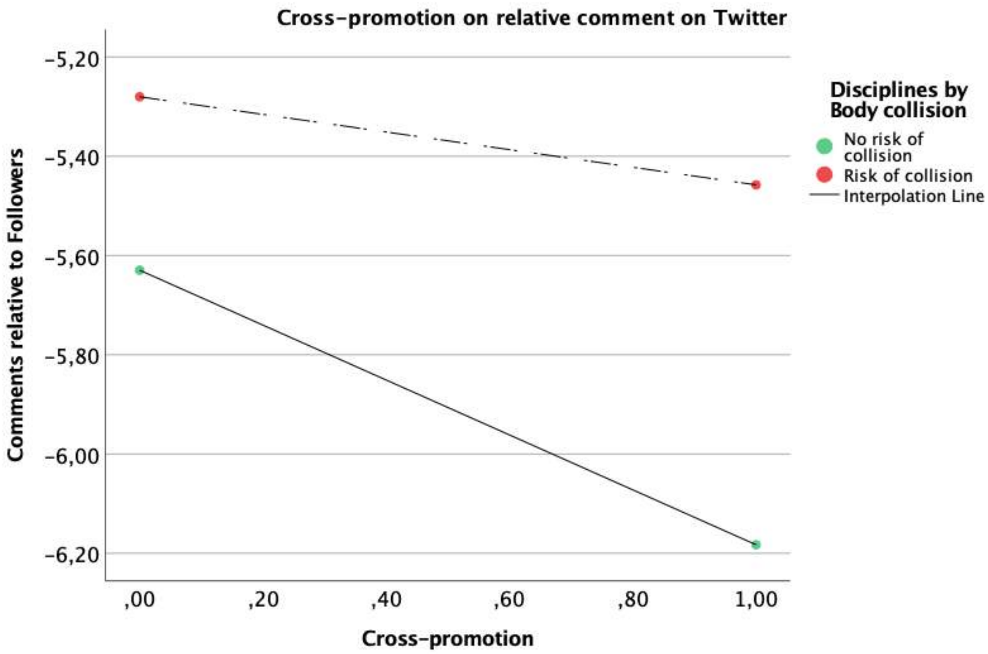


Table 34 *Quality* subdimensions on *likes* on Twitter

Quality subdimension	β	se	*t*	*p*	R^2
Production process	-0.23	0.38	-0.59	0.55	
bodycoll * Production	-0.23	0.46	-0.5	0.62	0.18
Development	-0.05	0.08	-0.58	0.56	
bodycoll *Development	0.01	0.11	0.05	0.96	0.18
Hooking	0.27	0.05	5.87	**0.00**	
bodycoll *Hooking	0.39	0.07	5.32	**0.00**	0.2
Stats	0.23	0.07	3.42	**0.00**	
bodycoll *Stats	0.06	0.12	0.53	0.6	0.18
Immersion	0.04	0.13	0.33	0.74	
bodycoll *Immersion	0.01	0.21	0.03	0.98	0.18
Bridging	0.17	0.08	2.17	**0.03**	
bodycoll *Bridging	0.36	0.1	3.44	**0.00**	0.19
Bridging People	-0.29	0.13	-2.29	**0.02**	
bodycoll *Bridging People	-0.10	0.21	-0.49	0.62	0.18
Healthy	-1.13	0.47	-2.43	**0.02**	
bodycoll *Healthy	-1.13	0.47	-2.43	**0.02**	0.19
Joyful	0.2	0.04	5.28	**0**	
bodycoll *Joyful	0.35	0.06	6.09	**0**	0.2
News	-0.08	0.04	-2.14	**0.03**	
bodycoll *News	-0.03	0.05	-0.59	0.56	0.18
Gallery	0.1	0.04	2.79	**0.01**	
bodycoll *Gallery	0.15	0.05	3.27	**0**	0.19
Highlights	-0.08	0.05	-1.56	0.12	
bodycoll *Highlights	0.01	0.08	0.08	0.93	0.18
N	1,616				
Mean	-3.77				
Standard Deviation	0.72				

Table 35 *Quality* subdimensions on *comments* on Twitter

Quality subdimension	β	se	*t*	*p*	R^2
Production process	-0.55	0.39	-1.41	0.16	
bodycoll * Production	-0.46	0.47	-0.97	0.33	0.1
Development	-0.28	0.09	-2.99	**0.00**	
bodycoll *Development	-0.16	0.13	-1.25	0.21	0.1
Hooking	0.1	0.05	1.94	**0.05**	
bodycoll *Hooking	0.37	0.08	4.45	**0.00**	0.11
Stats	0.00	0.08	0.02	0.98	
bodycoll *Stats	0.23	0.13	1.81	0.07	0.1
Immersion	0.01	0.15	0.06	0.95	
bodycoll *Immersion	0.18	0.3	0.58	0.57	0.1
Bridging	0.1	0.09	1.11	0.27	
bodycoll *Bridging	0.4	0.12	3.33	**0.00**	0.11
Bridging People	-0.23	0.15	-1.57	0.12	
bodycoll *Bridging People	0.00	0.24	0.02	0.99	0.1
Healthy	-0.71	0.68	-1.04	0.3	
bodycoll *Healthy	-0.71	0.68	-1.04	0.3	0.1
Joyful	0.01	0.05	0.26	0.8	
bodycoll *Joyful	0.35	0.07	5.2	**0.00**	0.12
News	0.09	0.05	1.82	0.07	
bodycoll *News	0.5	0.06	8.93	**0.00**	0.16
Gallery	0.09	0.04	2.2	**0.03**	
bodycoll *Gallery	0.24	0.06	4.43	**0.00**	0.11
Highlights	-0.03	0.06	-0.5	0.62	
bodycoll *Highlights	0.08	0.09	0.87	0.38	0.1
N	1,133				
Mean	-5.48				
Standard Deviation	0.7				

Below, the strength of the relationships varies but the direction is the same. For both *collision* and non-collision sports, engagement increases for the following *quality* subdimensions : *Hooking* (on likes and comments), *Gallery* (on comments), *Bridging* (on likes) and *Joyful* (on likes).

Fig. 59 Impact of *Hooking* on *relative likes* on Twitter

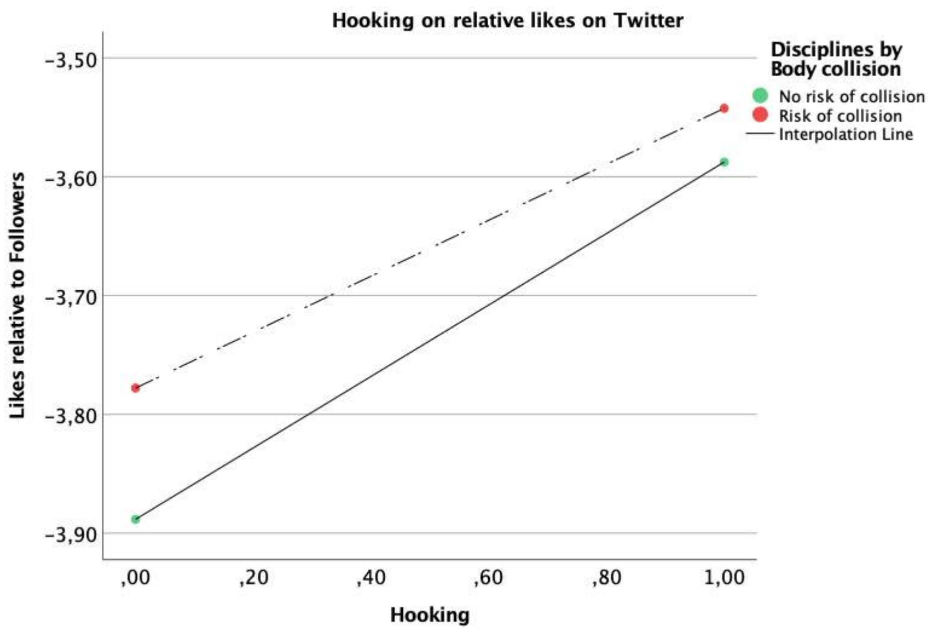


Fig. 60 Impact of *Hooking* on *relative comments* on Twitter

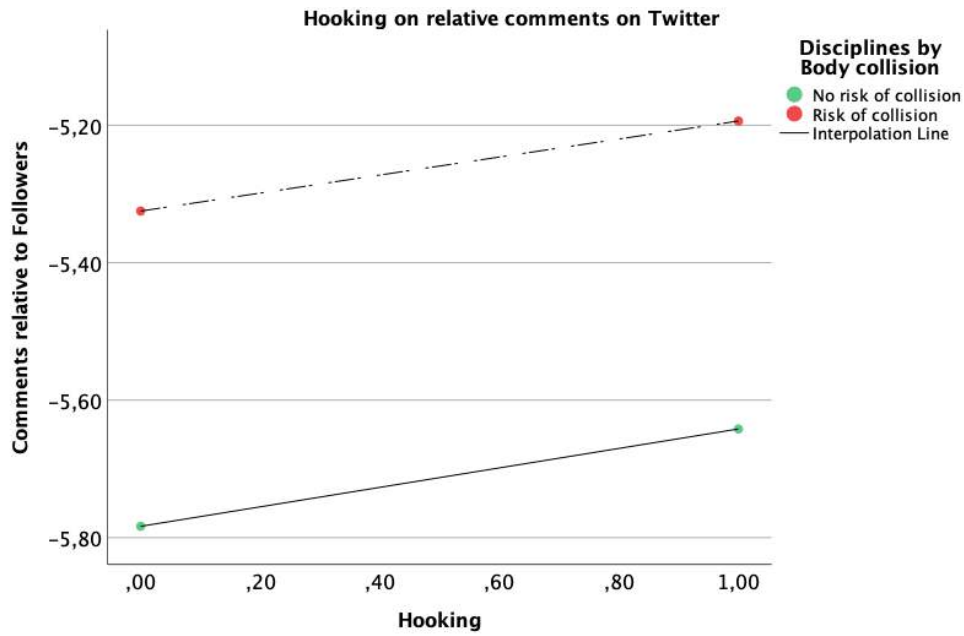


Fig. 61 Impact of *Gallery* on *relative comments* on Twitter

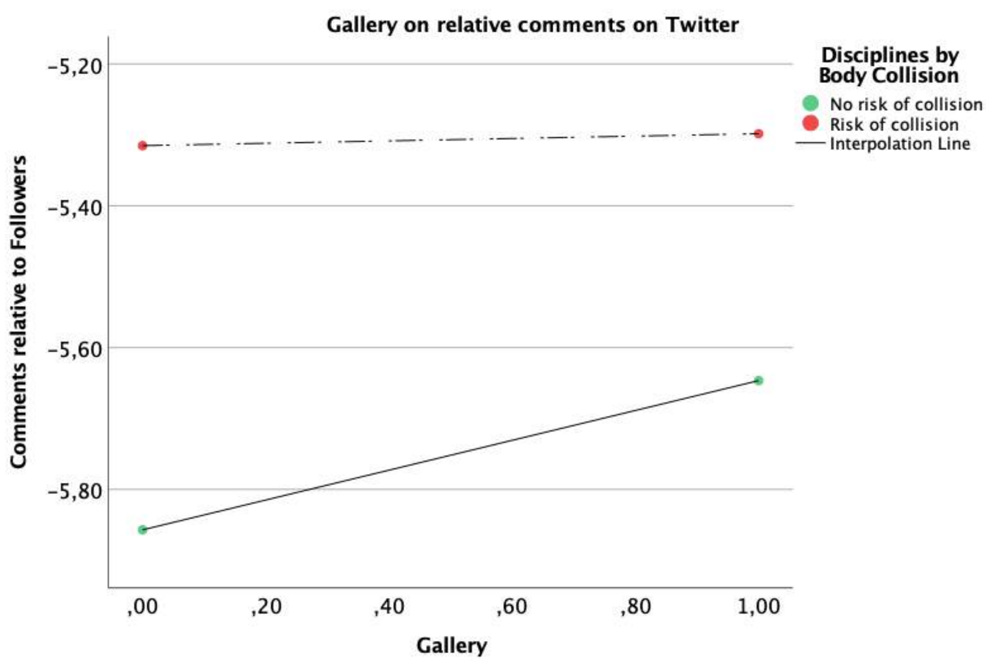


Fig. 62 Impact of *Gallery* on *comments* on Twitter

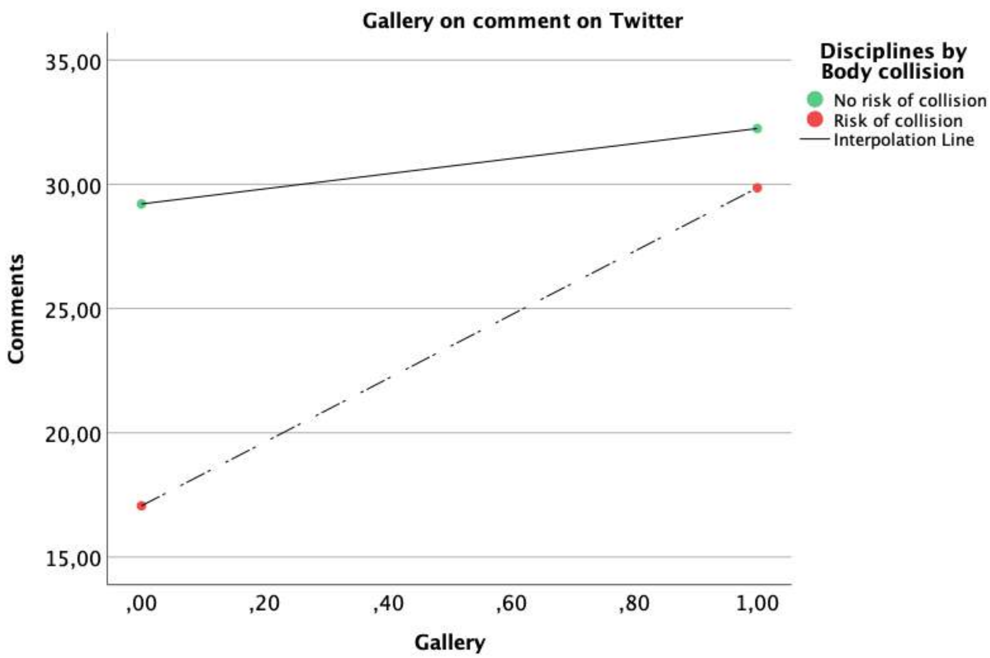


Fig. 63 Impact of *Bridging* on *relative likes* on Twitter

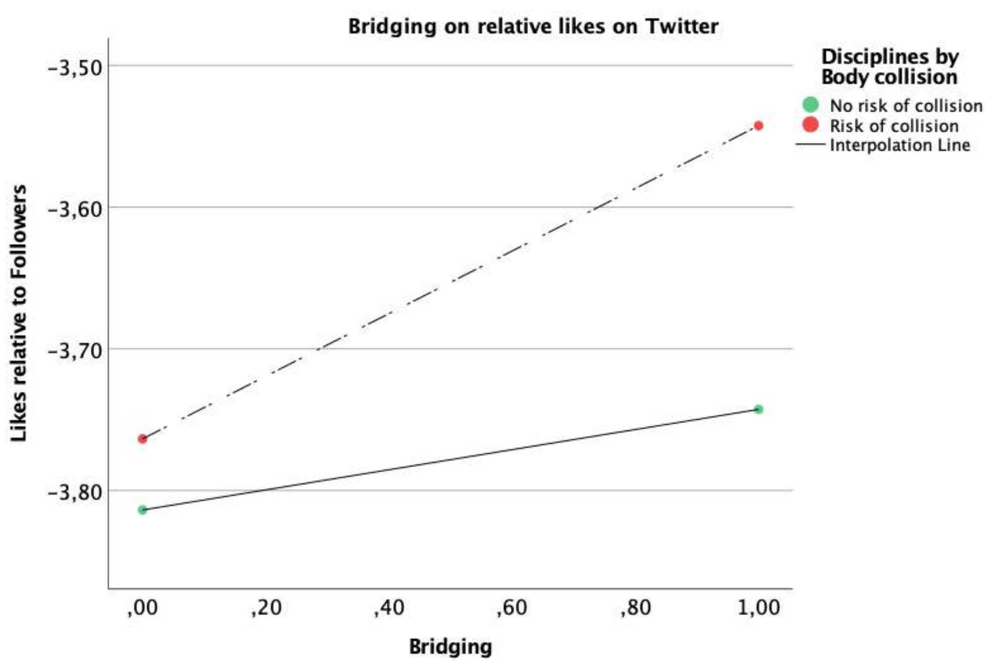
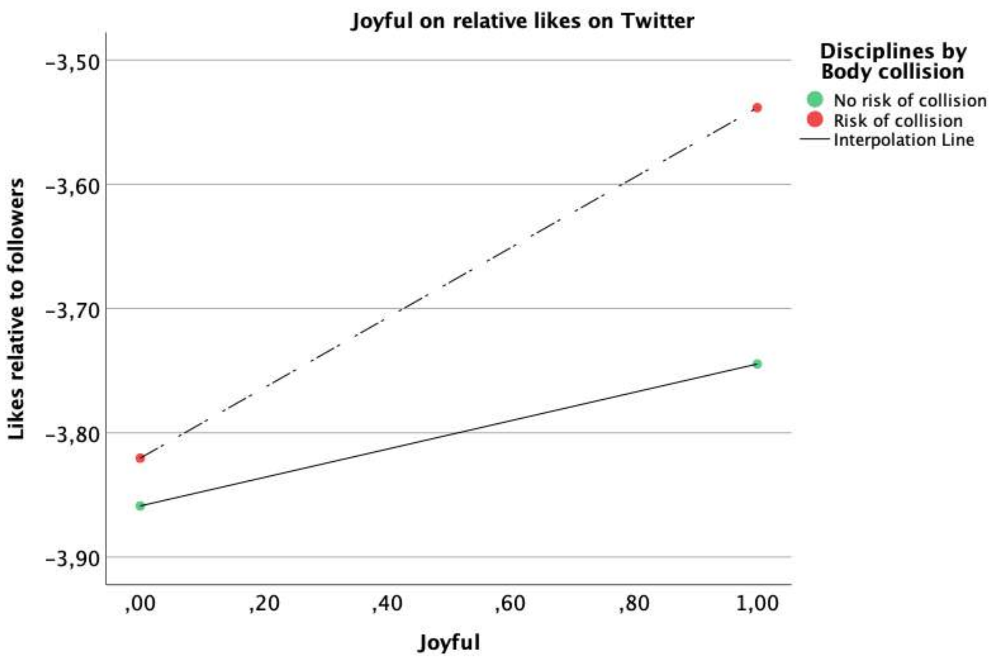


Fig. 64 Impact of *Joyful* on *relative likes* on Twitter



In the examples below, the direction of the two groups is diametrically opposed. For *collision* sports, comments increase as the content of *Bridging*, *Joyful* or *News* increase. The same goes for likes which climb as the *Gallery* content increases. For collision-free sports, the effect is the opposite, as when these contents increase, the corresponding comments and likes decrease. In other words, the effect of these subdimensions on engagement performance significantly depend on *body collision*.

Fig. 65 Impact of *Bridging* on *relative comments* on Twitter

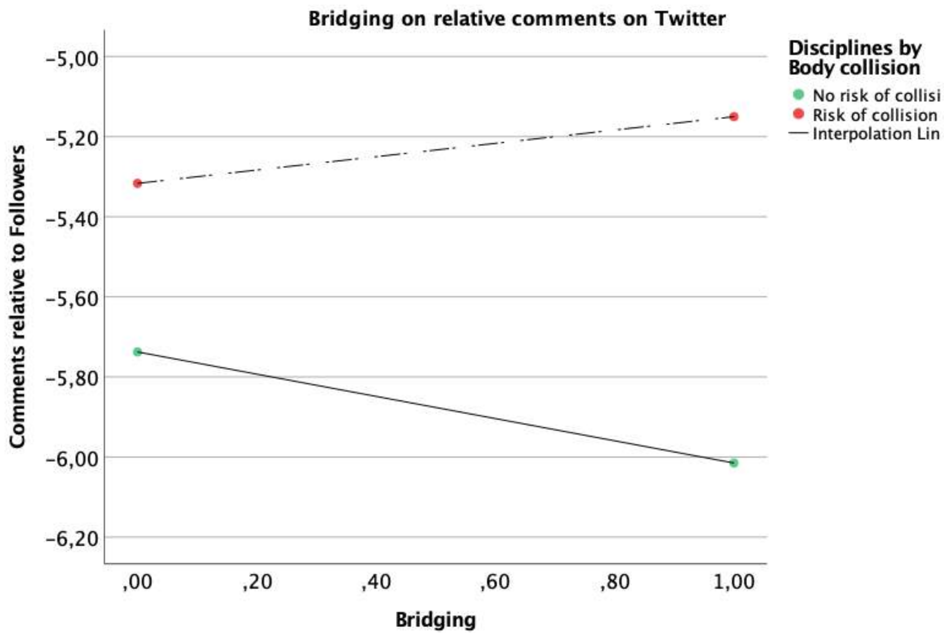


Fig. 66 Impact of *Bridging* on absolute *comments* on Twitter

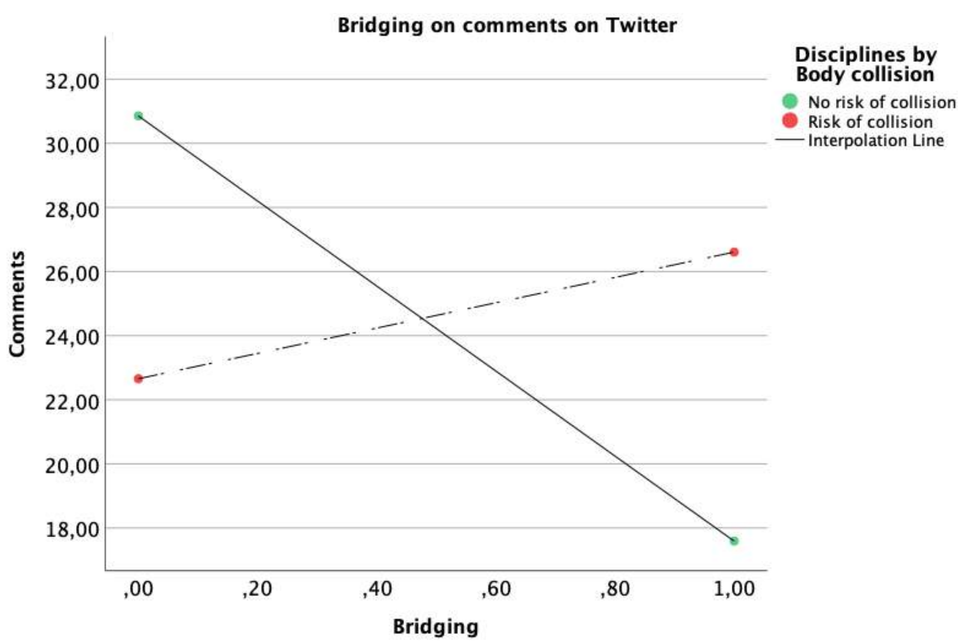


Fig. 67 Impact of *Joyful* on *relative comments* on Twitter

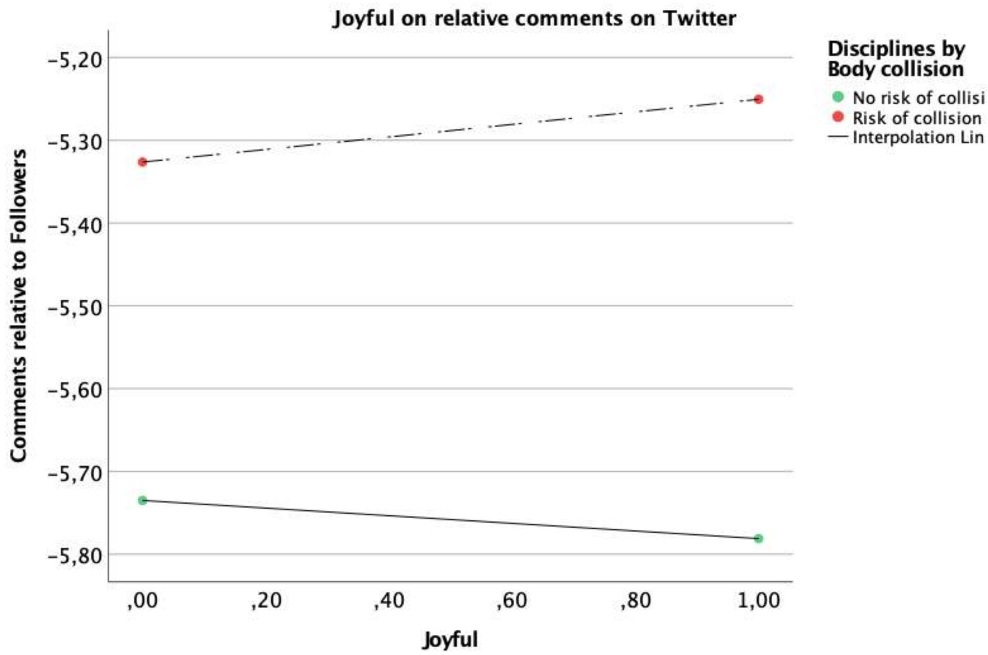


Fig. 68 Impact of *News* on *relative comments* on Twitter

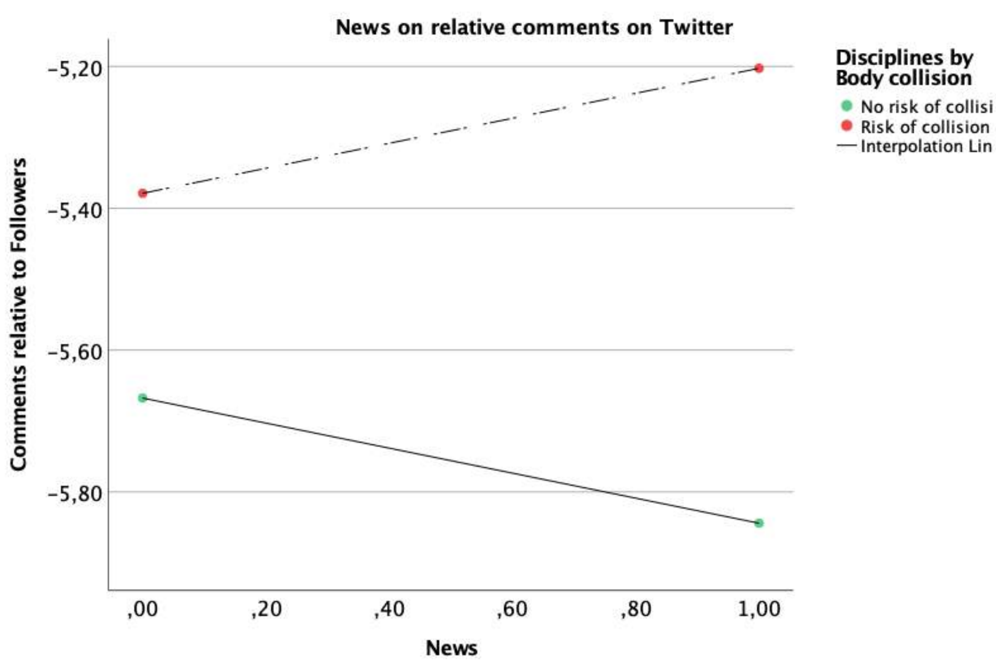
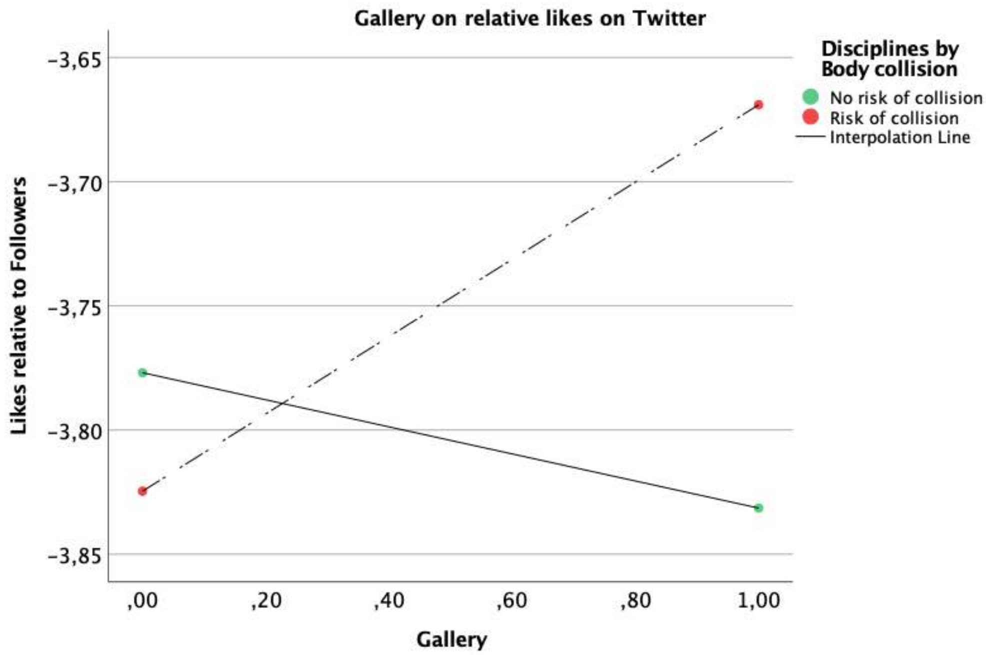


Fig. 69 Impact of *Gallery* on *relative likes* on Twitter



***Social* subdimensions on Twitter :**

Table 36 *Social* subdimensions on *likes* on Twitter

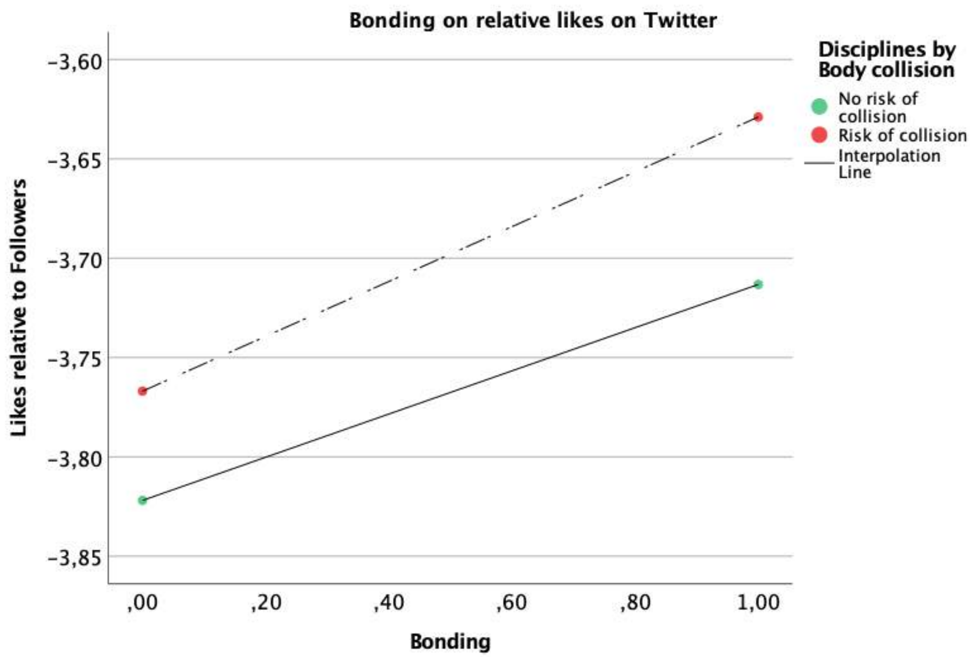
Social subdimensions	β	se	*t*	*p*	R^2
Bonding	0.11	0.05	2.1	**0.04**	
bodycoll * Bonding	0.18	0.07	2.43	**0.02**	0.18
Evangelization					
bodycoll *Evangelization					
Defending	-0.1	0.1	-0.93	0.36	
bodycoll *Defending	0.09	0.15	0.62	0.54	0.18
Social Spotlight	0.17	0.21	0.83	0.41	
bodycoll *Social Spotlight	0.25	0.23	1.08	0.28	0.18
Small Talk	-0.12	0.13	-0.87	0.39	
bodycoll *Small Talk	-0.02	0.17	-0.11	0.91	0.18
Intimacy	0.14	0.07	1.9	0.06	
bodycoll *Intimacy	0.25	0.13	1.88	0.06	0.18
Behind-the-scenes	0.03	0.05	0.7	0.48	
bodycoll *Behind-the-scenes	0.1	0.07	1.41	0.16	0.18
Crowdsourcing	-0.05	0.05	-0.94	0.35	
bodycoll *Crowdsourcing	-0.01	0.08	-0.16	0.87	0.18
Charity	-0.38	0.11	-3.41	**0.00**	
bodycoll *Charity	0.04	0.16	0.25	0.8	0.18
N	1,617				
Mean	-3.77				
Standard Deviation	0.72				

Table 37 *Social* subdimensions on *comments* on Twitter

Social subdimensions	β	se	*t*	*p*	R^2
Bonding	0.08	0.06	1.24	0.22	
bodycoll * Bonding	0.32	0.09	3.67	**0.00**	0.1
Evangelization					
bodycoll *Evangelization					
Defending	-0.2	0.13	-1.53	0.13	
bodycoll *Defending	-0.04	0.18	-0.23	0.82	0.09
Social Spotlight	0.48	0.28	1.75	0.08	
bodycoll *Social Spotlight	0.44	0.3	1.46	0.14	0.09
Small Talk	-0.23	0.16	-1.44	0.15	
bodycoll *Small Talk	-0.15	0.21	-0.74	0.46	0.09
Intimacy	-0.05	0.08	-0.63	0.53	
bodycoll *Intimacy	0.26	0.17	1.58	0.12	0.09
Behind-the-scenes	-0.24	0.06	-4.21	**0.00**	
bodycoll *Behind-the-scenes	0.01	0.09	0.16	0.88	0.09
Crowdsourcing	0.00	0.06	-0.07	0.95	
bodycoll *Crowdsourcing	0.23	0.09	2.49	**0.01**	0.09
Charity	-0.34	0.16	-2.07	**0.04**	
bodycoll *Charity	0.13	0.24	0.55	0.58	0.09
N	1,133				
Mean	-5.48				
Standard Deviation	0.7				

As for the *social* dimension, the risk of *collision* in sports changes the relationship between the subdimensions and user online engagement in only three cases. The first case is *Bonding* content which increases the number of likes among both groups.

Fig. 70 Impact of *Bonding* on *relative likes* on Twitter



The second case is that of *Bonding* on the number of comments. Increasing *Bonding* content leads to more comments among *collision* sports followers, and less among collisionfree sports followers, the difference is more obvious in absolute numbers.

Fig. 71 Impact of *Bonding* on *relative comments* on Twitter

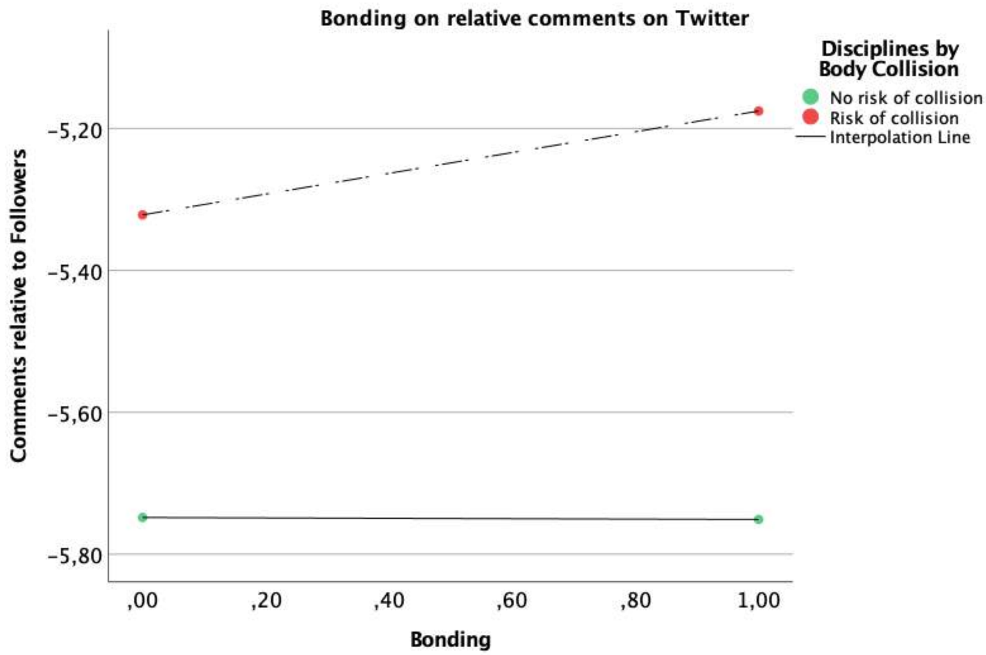
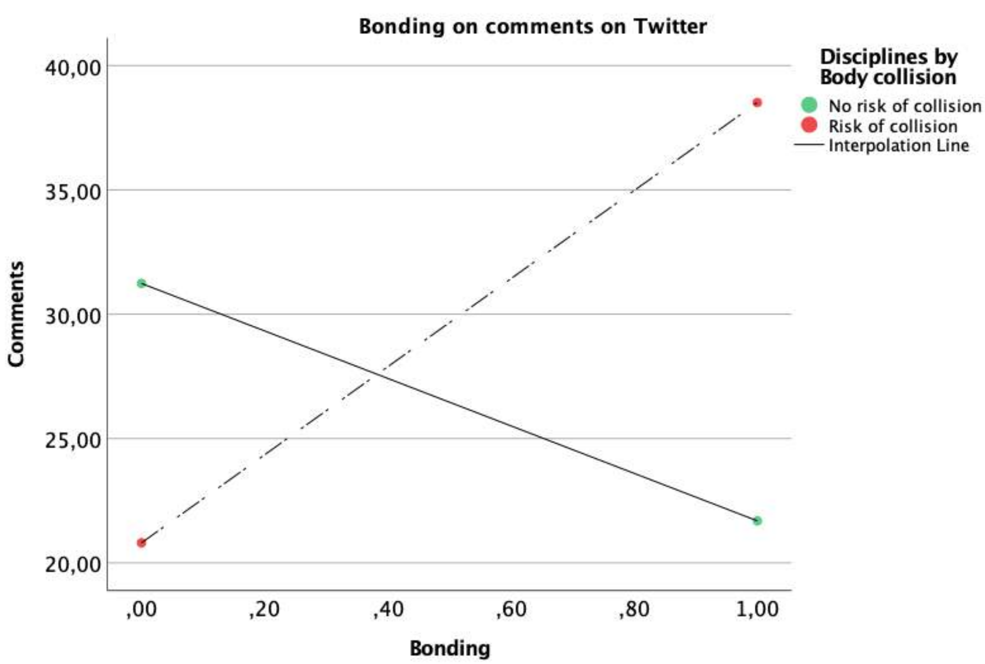


Fig. 72 Impact of *Bonding* on absolute *comments* on Twitter



The third case is that of *Crowdsourcing* on the number of comments. Much like *Bonding*, it increases the number of comments among *collision* sports followers, but decreases them among non-collision sports fans.

Fig. 73 Impact of *Crowdsourcing* on *relative comments* on Twitter

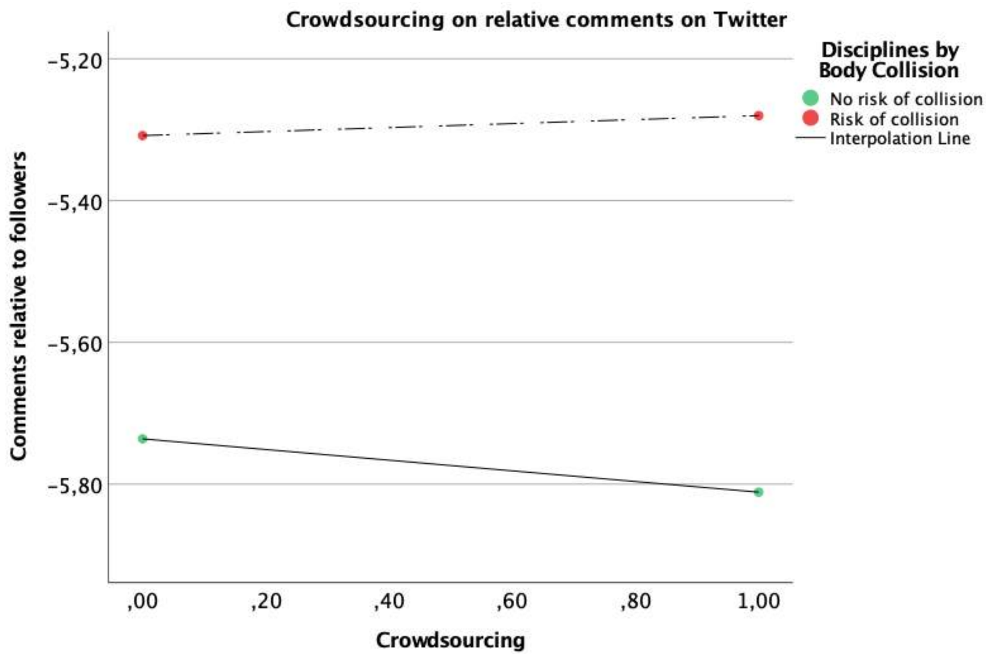


Fig. 74 Impact of *Crowdsourcing* on *absolute comments* on Twitter

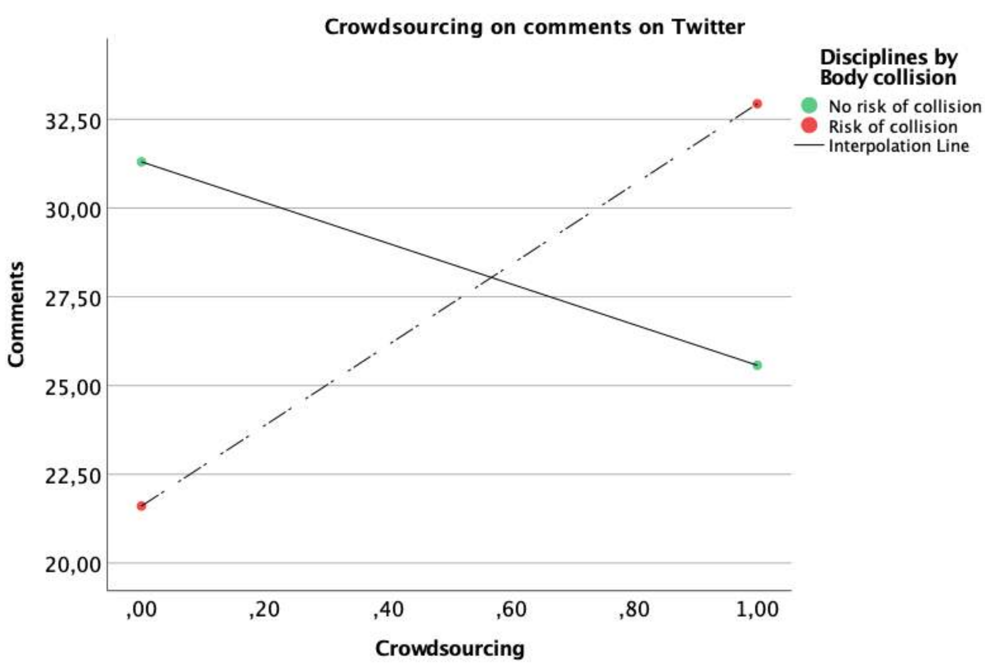


Table 38 *Selling* subdimension on *likes* on Facebook

Selling subdimensions	β	se	*t*	*p*	R^2
Explicit selling	-0.22	0.07	-3.35	**0.00**	
bodycoll*Explicit	-0.06	0.09	-0.62	0.54	0.12
Implicit selling	-0.14	0.03	-4.53	**0.00**	
bodycoll*Implicit	0.02	0.04	0.43	0.66	0.12
Product	-0.35	0.08	-4.58	**0.00**	
bodycoll*Product	-0.3	0.1	-2.87	**0.00**	0.13
Price	0.27	0.4	0.68	0.5	
bodycoll*Price	0.27	0.4	0.68	0.5	0.12
Subscrip	-0.24	0.12	-2.03	**0.04**	
bodycoll*Suscrip	-0.32	0.17	-1.89	0.06	0.13
EventMarketing	-0.42	0.12	-3.43	**0.00**	
bodycoll*EventM	-0.23	0.15	-1.53	0.13	0.12
EventsTickets	-0.13	0.03	-3.91	**0.00**	
bodycoll*EventT	-0.07	0.04	-1.55	0.12	0.12
PrizeDraws	-0.43	0.13	-3.32	**0.00**	
bodycoll*PrizeDraws	-0.06	0.17	-0.33	0.74	0.12
CrossPromo	-0.1	0.05	-2.18	**0.03**	
bodycoll * Cross	0.23	0.06	3.66	**0.00**	0.13
Mean	-3.32				
Standard Deviation	0.6				
N	1,449				

Table 39 *Selling* subdimension on *comments* on Facebook

Selling subdimensions	β	se	*t*	*p*	R^2
Explicit selling	0.00	0.09	0.03	0.98	
bodycoll*Explicit	0.27	0.12	2.26	**0.02**	0.11
Implicit selling	-0.18	0.04	-4.46	**0.00**	
bodycoll*Implicit	0.19	0.06	3.41	**0.00**	0.11
Product	-0.14	0.1	-1.41	0.16	
bodycoll*Product	0.2	0.14	1.46	0.15	0.11
Price	0.72	0.52	1.37	0.17	
bodycoll*Price	0.72	0.523	1.37	0.17	0.11
Subscrip	-0.2	0.15	-1.33	0.18	
bodycoll*Suscrip	-0.12	0.23	-0.55	0.58	0.11
EventMarketing	-0.16	0.16	-0.98	0.33	
bodycoll*EventM	0.21	0.19	1.08	0.28	0.11
EventsTickets	-0.08	0.04	-1.94	**0.05**	
bodycoll*EventT	0.17	0.06	3.00	**0.00**	0.11
PrizeDraws	-0.42	0.17	-2.48	**0.01**	
bodycoll*PrizeDraws	0.12	0.22	0.54	0.59	0.11
CrossPromo	-0.21	0.06	-3.55	**0.00**	
bodycoll * Cross	0.19	0.08	2.4	**0.02**	0.11
Mean	1,546				
Standard Deviation	-4.68				
N	0.78				

By converting the initial engagement numbers to relative to followers' measures and then processing the data through a Log10 transformation, *Explicit Selling* in *collision* sports increases very slightly the number of comments, so does *Cross-Promotion* on likes.

By redoing the regressions in absolute numbers, they both clearly decrease engagement with a steep slope. As the Log transformation de-emphasizes outliers, the discrepancy between these two suggests that, in terms of absolute numbers, some *Explicit Selling* publications and *Cross-Promotions* significantly lower engagement levels (Metcalf and William, 2016).

Fig. 75 Impact of *Explicit Selling* on *relative comments* on Facebook

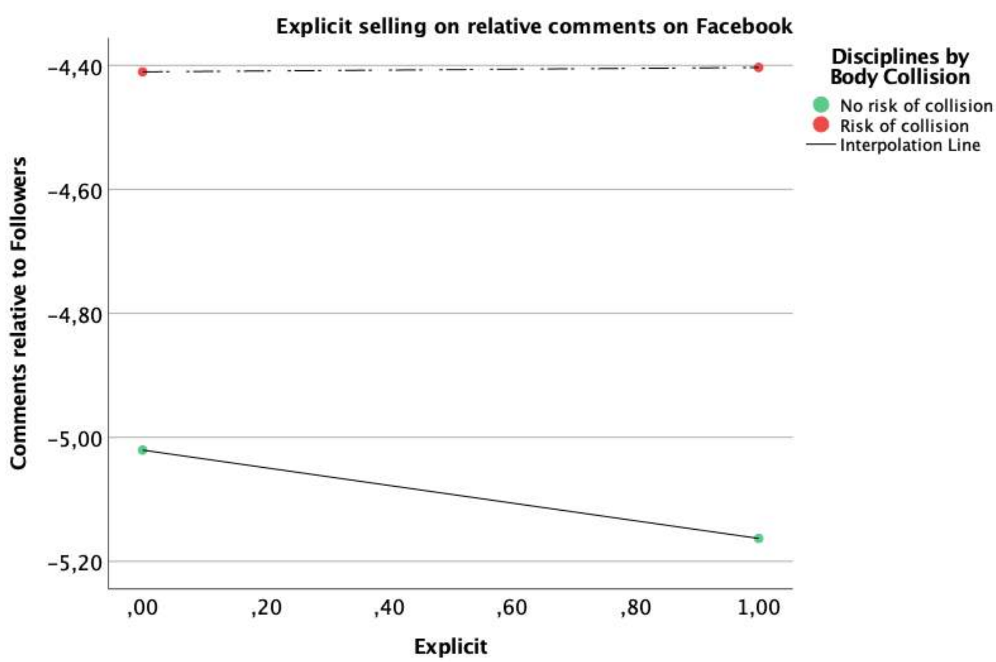


Fig. 76 Impact of *Explicit Selling* on *absolute comments* on Facebook

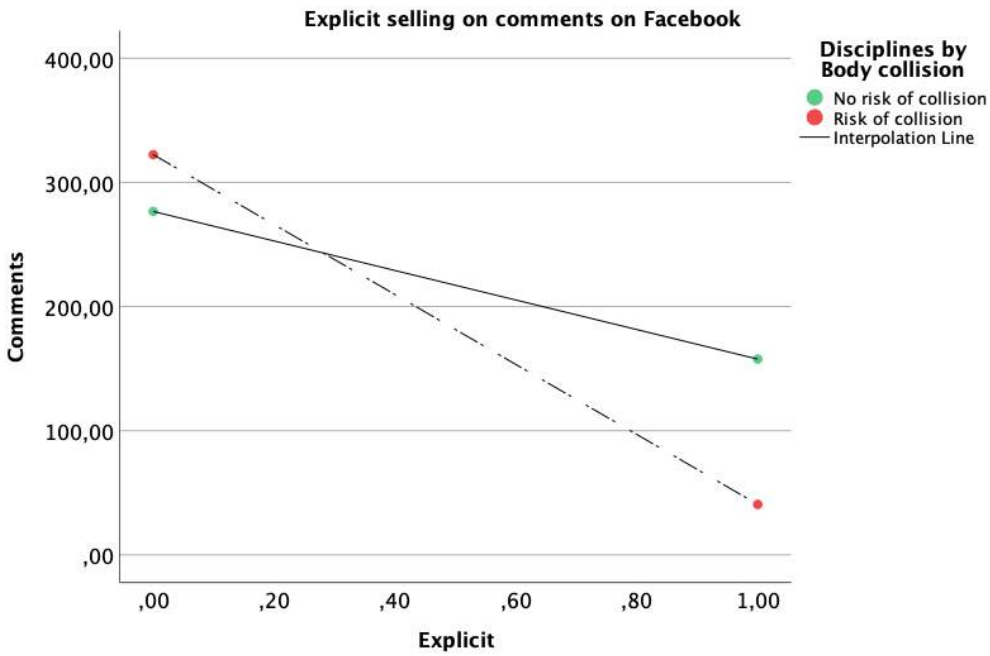


Fig. 77 Impact of *Cross-Promotion* on *relative likes* on Facebook

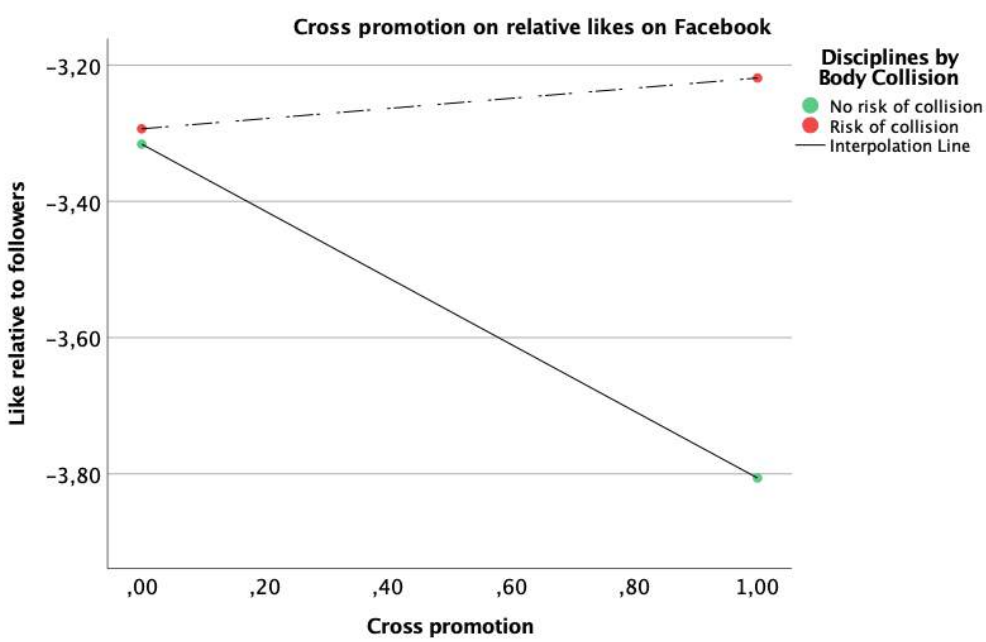
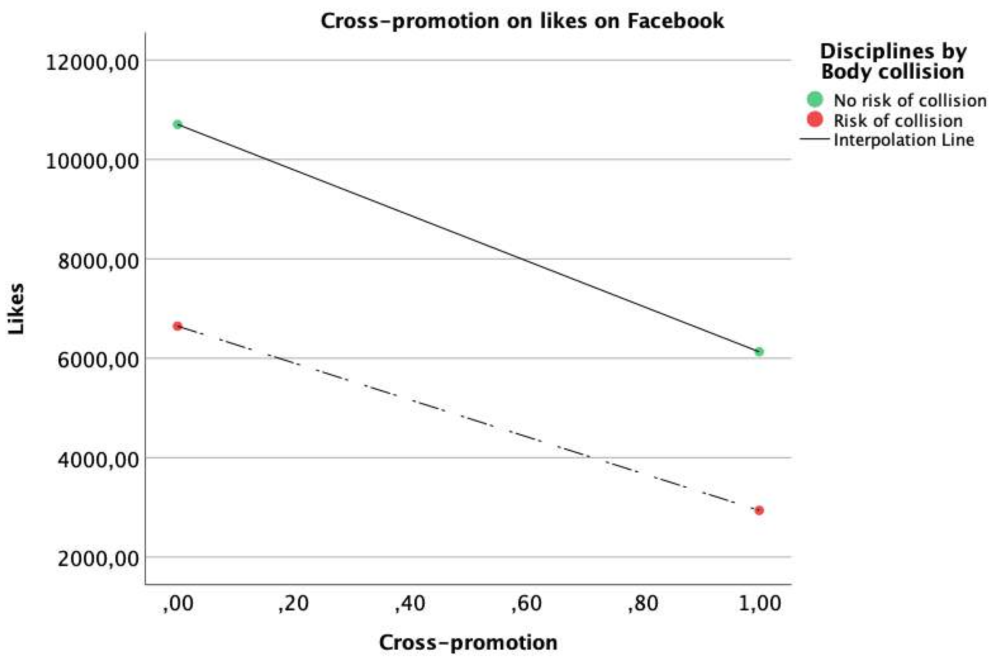


Fig. 78 Impact of *Cross-Promotion* on absolute likes on Facebook



On Facebook, the influence of *selling* subdimensions on engagement varies in intensity according to the risk of *collision*, but whether it is *Explicit Selling* (on comments), *Cross-Promotion* (on likes and comments), *Implicit Selling* (on comments), *Product/Family Promotion* (on likes) or *Events Tickets* (on comments), all decrease engagement regardless of the sport followed.

Fig. 79 Impact of *Cross-Promotion* on *relative comments* on Facebook

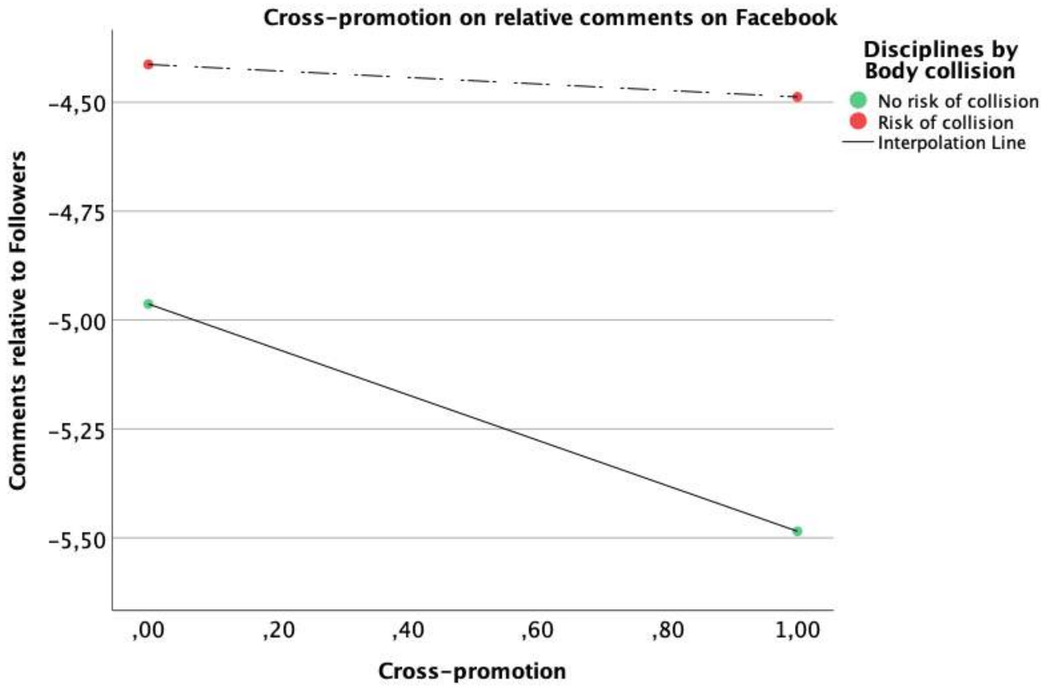


Fig. 80 Impact of *Cross-Promotion* on absolute comments on Facebook

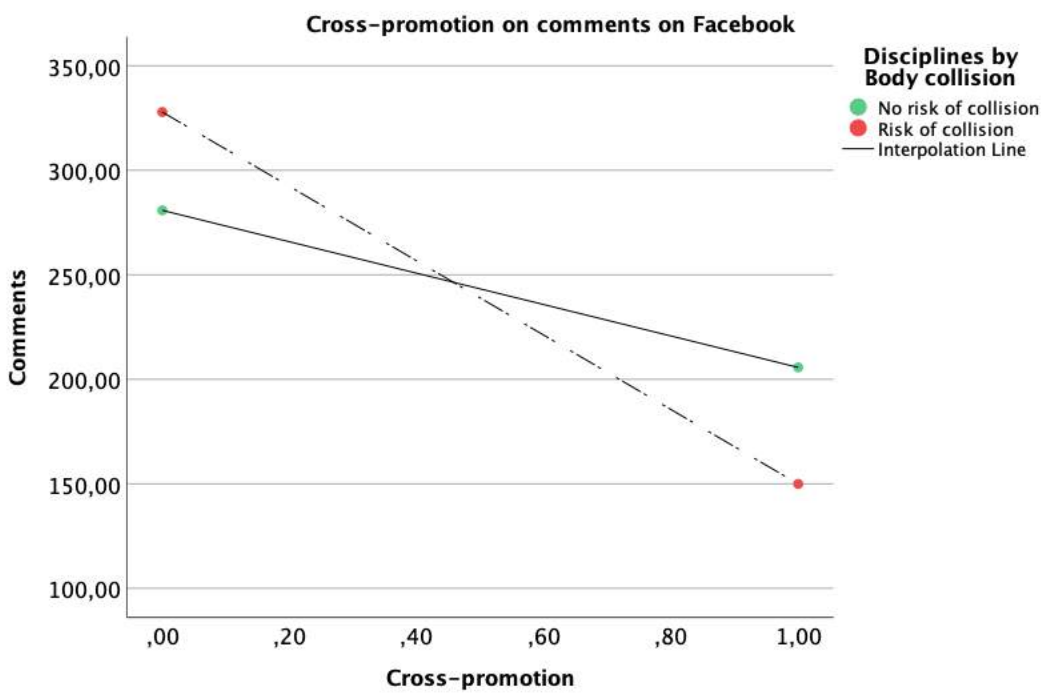


Fig. 81 Impact of *Implicit Selling* on *relative comments* on Facebook

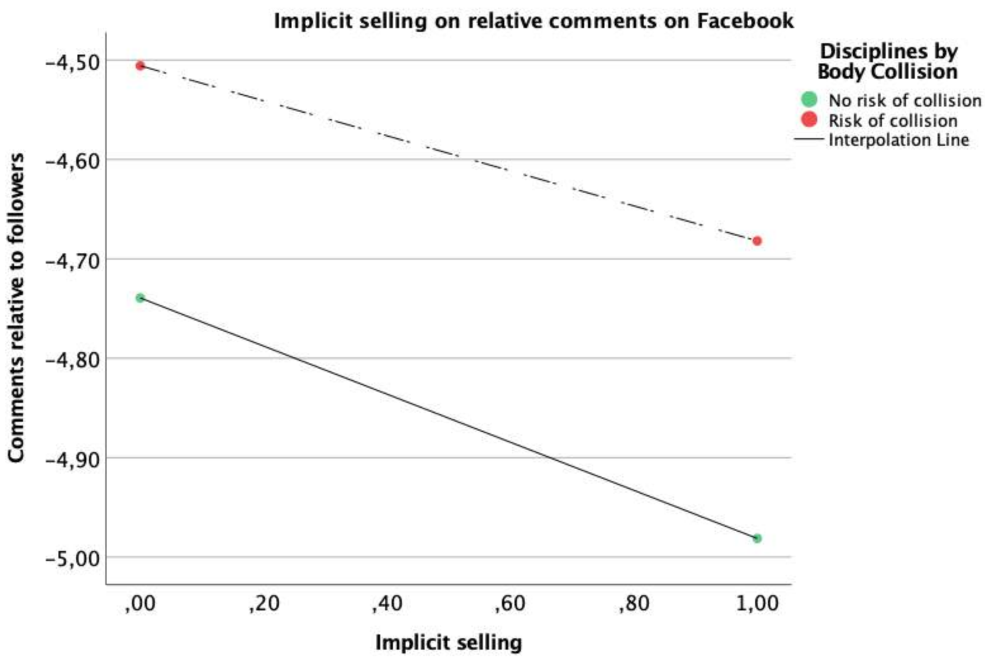


Fig. 82 Impact of *Product/Family* on *relative likes* on Facebook

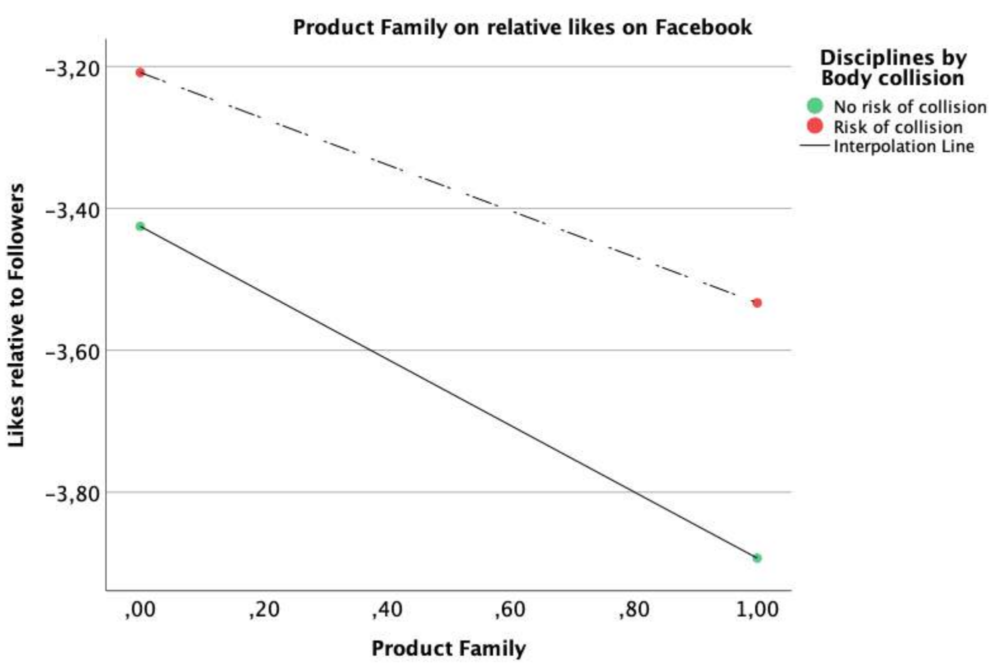


Fig. 83 Impact of *Events/Tickets* on *relative comments* on Facebook

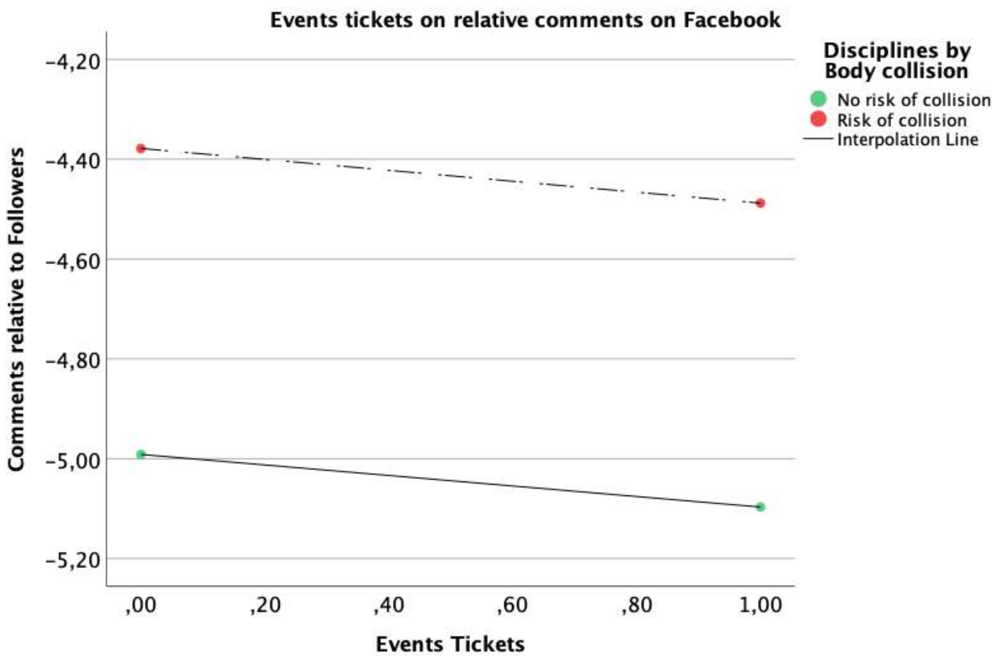


Fig. 84 Impact of *Events/Tickets* on absolute comments on Facebook

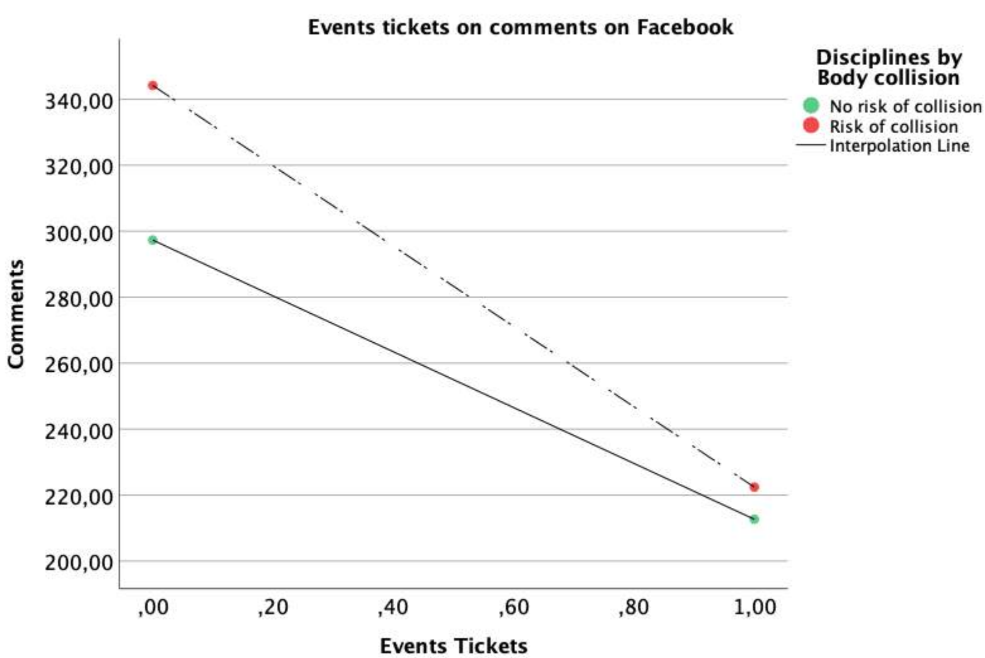


Table 40 *Quality* subdimensions on *likes* on Facebook

Quality subdimension	β	se	*t*	*p*	R^2
Production process					
bodycoll * Production					
Development	-0.28	0.06	-4.45	**0.00**	
bodycoll *Development	-0.36	0.09	-4.21	**0.00**	0.13
Hooking	0.09	0.04	2.23	**0.026**	
bodycoll *Hooking	0.26	0.08	3.32	**0**	0.13
Stats	-0.23	0.06	-4.21	**0.00**	
bodycoll *Stats	-0.26	0.08	-3.32	**0**	0.13
Immersion	-0.21	0.07	-2.97	**0**	
bodycoll *Immersion	-0.11	0.1	-1.14	0.25	0.12
Bridging	-0.07	0.08	-0.83	0.41	
bodycoll *Bridging	0.32	0.15	2.09	**0.04**	0.13
Bridging People	-0.02	0.13	-0.16	0.88	
bodycoll *Bridging People	0.13	0.2	0.66	0.51	0.12
Healthy	0.02	0.4	0.04	0.97	
bodycoll *Healthy					
Joyful	0.09	0.03	2.75	**0.01**	
bodycoll *Joyful	0.22	0.05	4.48	**0**	0.14
News	0.14	0.04	3.74	**0**	
bodycoll *News	0.27	0.05	5.45	**0**	0.14
Gallery	0.1	0.03	3.39	**0**	
bodycoll *Gallery	0.22	0.04	5.81	**0**	0.14
Highlights	0.08	0.04	1.84	0.07	
bodycoll *Highlights	0.22	0.06	3.98	**0**	0.13
N	1,449				
Mean	-3.32				
Standard Deviation	0.6				

Table 41 *Quality* subdimensions on *comments* on Facebook

Quality subdimension	β	se	*t*	*p*	R^2
Production process					
bodycoll * Production					
Development	-0.37	0.08	-4.46	**0.00**	
bodycoll *Development	-0.26	0.11	-2.37	**0.02**	0.11
Hooking	-0.02	0.05	-0.29	0.78	
bodycoll *Hooking	0.31	0.1	3.04	**0**	0.11
Stats	-0.19	0.07	-2.64	**0.01**	
bodycoll *Stats	0.02	0.1	0.21	0.84	0.11
Immersion	-0.24	0.09	-2.68	**0.01**	
bodycoll *Immersion	-0.1	0.12	-0.8	0.42	0.11
Bridging	-0.33	0.1	-3.31	**0**	
bodycoll *Bridging	0.29	0.2	1.44	0.15	0.11
Bridging People	-0.13	0.17	-0.79	0.43	
bodycoll *Bridging People	0.3	0.26	1.15	0.25	0.11
Healthy	0.18	0.37	0.47	0.64	
bodycoll *Healthy					
Joyful	-0.05	0.04	-1.12	0.26	
bodycoll *Joyful	0.21	0.07	3.21	**0**	0.11
News	0.27	0.05	5.8	**0.00**	
bodycoll *News	0.62	0.06	9.79	**0.00**	0.16
Gallery	0.03	0.04	0.73	0.46	
bodycoll *Gallery	0.4	0.05	8.17	**0.00**	0.14
Highlights	0.08	0.05	1.4	0.16	
bodycoll *Highlights	0.36	0.07	4.98	**0**	0.12
N	1,546				
Mean	-4.68				
Standard Deviation	0.78				

In the examples below, the effect on engagement performance significantly depends on *body collision*. As *Bridgin*g content increases, likes increase in *body collision* sports and decrease in non-collision sports. The effect is exactly the opposite for content that is *Joyful* or features *Hooking* or *Highlights* on comments ; as contents increase, comments increase for non-collision sports followers and decrease for *collision* sports followers.

Fig. 85 Impact of *Bridging* on *relative likes* on Facebook

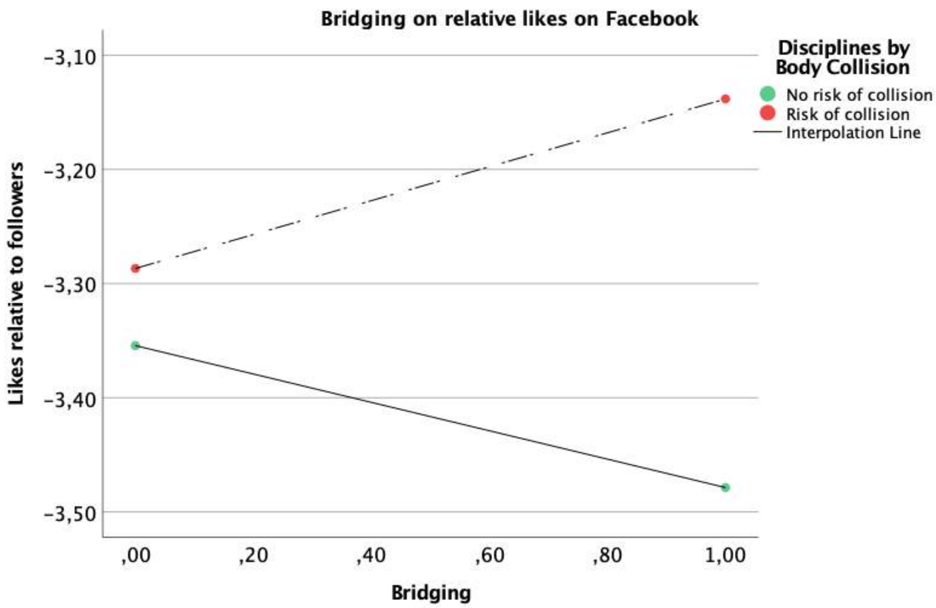


Fig. 86 Impact of *Bridging* on *absolute likes* on Facebook

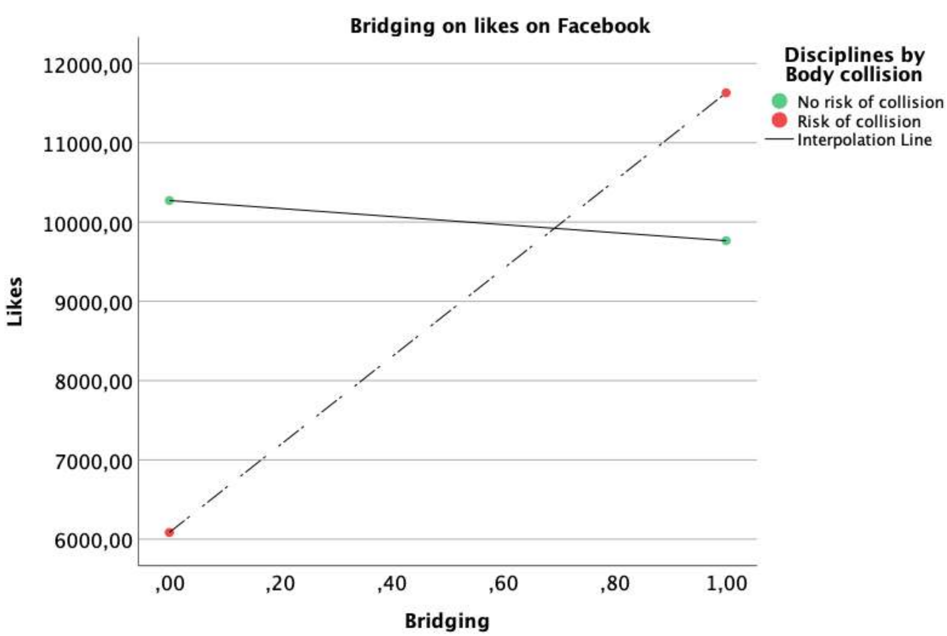


Fig. 87 Impact of *Hooking* on *relative comments* on Facebook

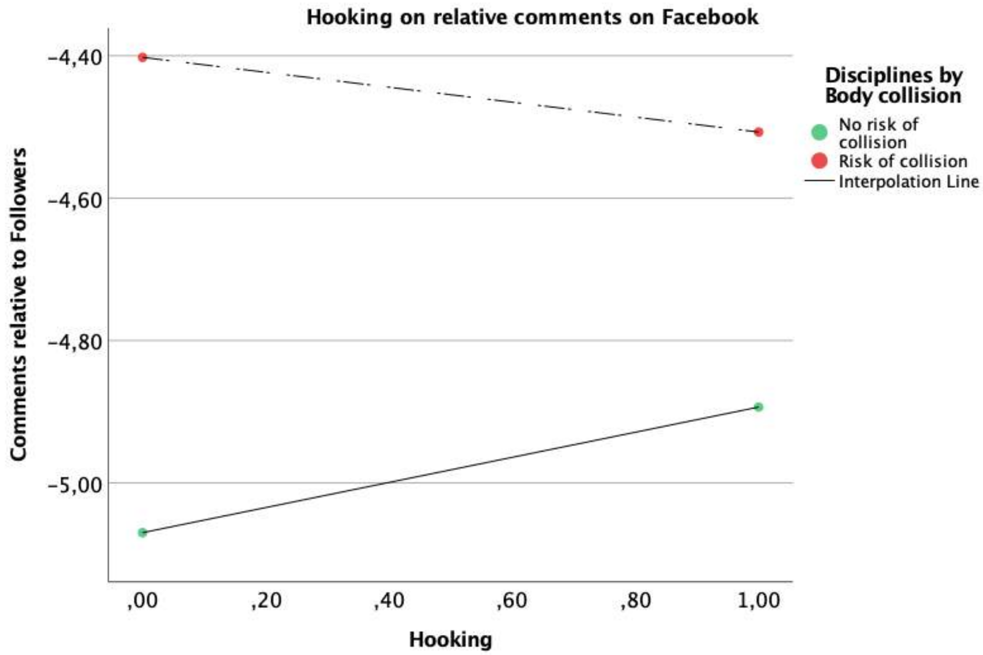


Fig. 88 Impact of *Highlights* on *relative comments* on Facebook

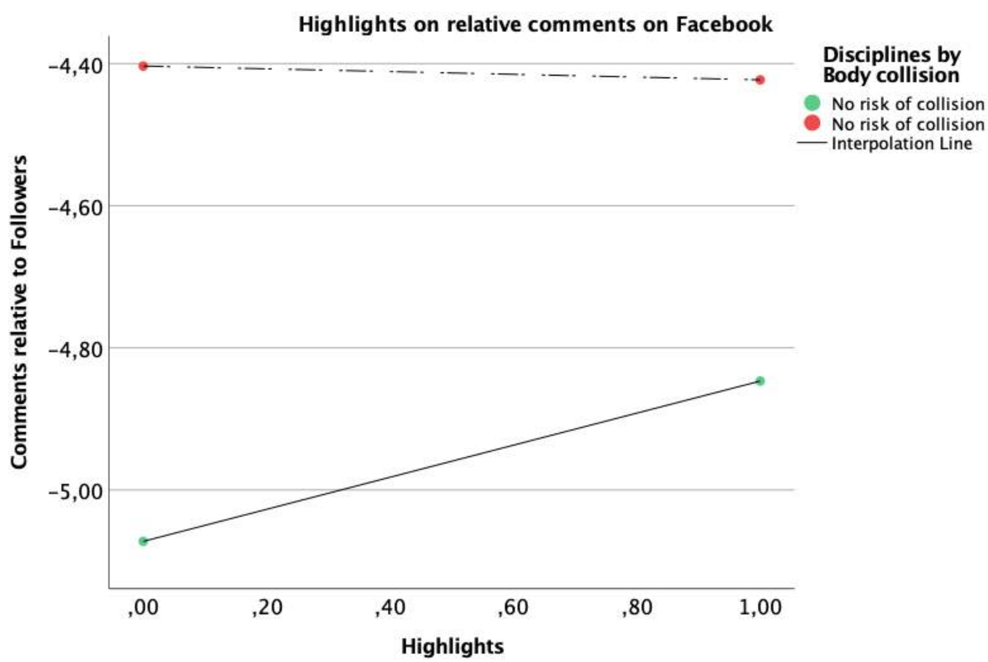


Fig. 89 Impact of *Highlights* on *absolute comments* on Facebook

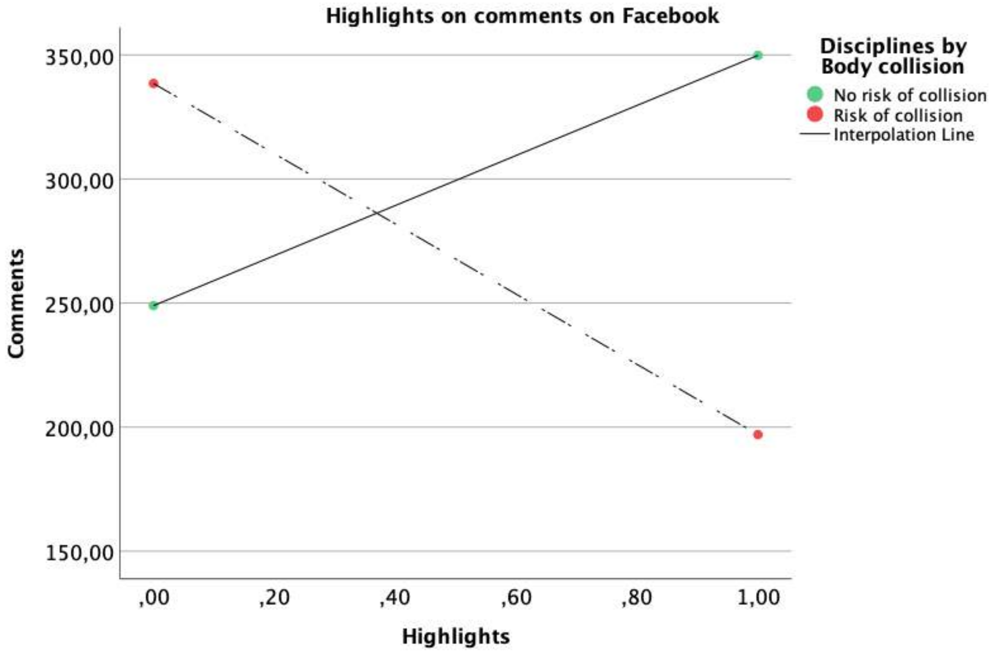


Fig. 90 Impact of *Joyful* on *relative comments* on Facebook

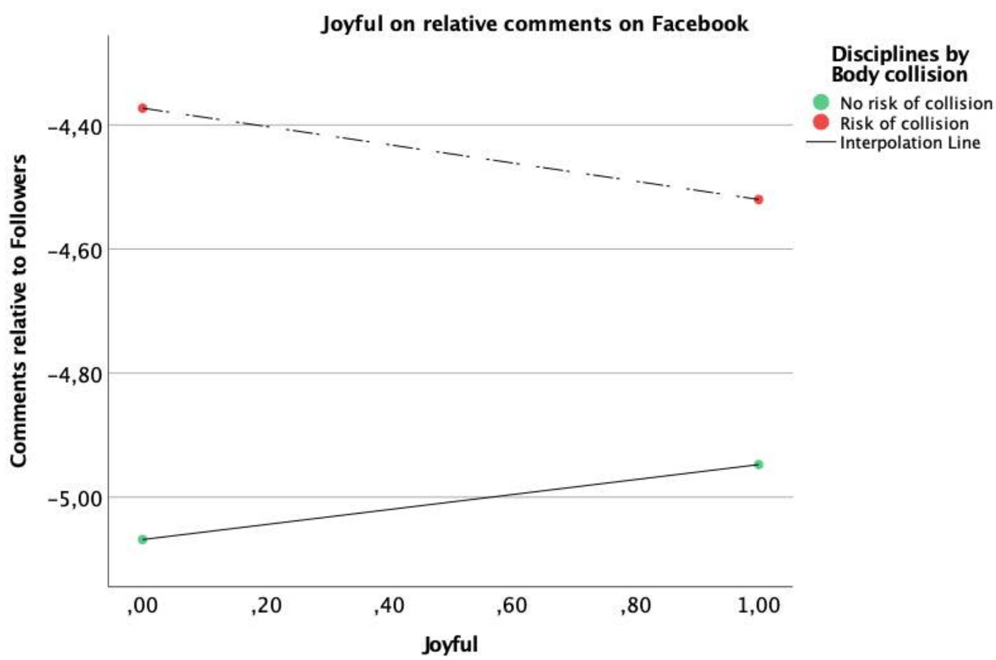
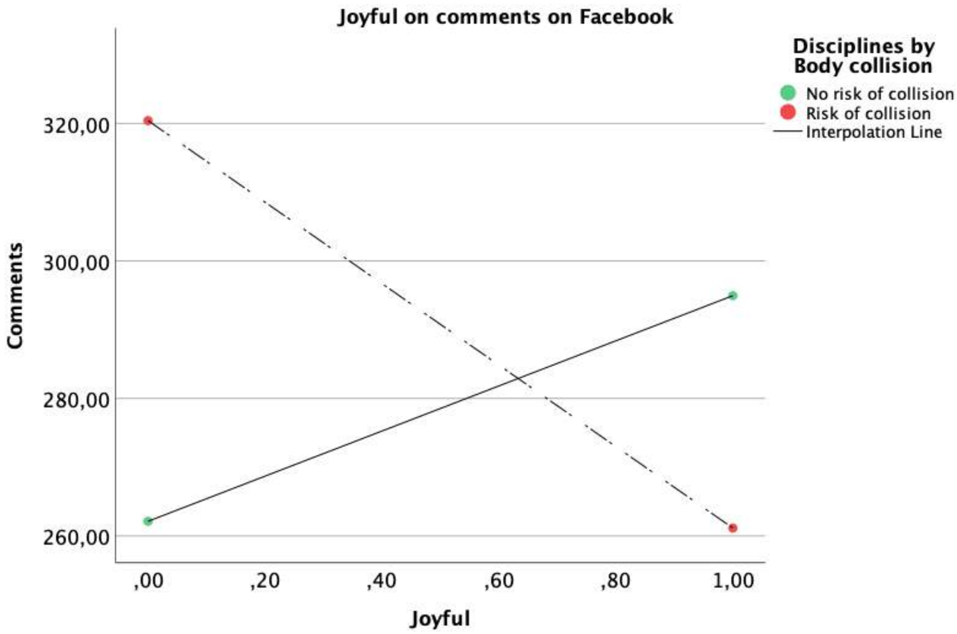


Fig. 91 Impact of *Joyful* on *comments* on Facebook



When the *quality* dimension is not studied as a homogeneous block, the following content subdimensions stand out as those increasing engagement among *collision* and non-collision sports followers, with variances in intensity : *Highlights* (on likes), *Hooking* (on likes), *News* (on likes and comments), *Gallery* (on likes and comments) and *Joyful* (on likes).

Fig. 92 Impact of *Highlights* on *relative comments* on Facebook

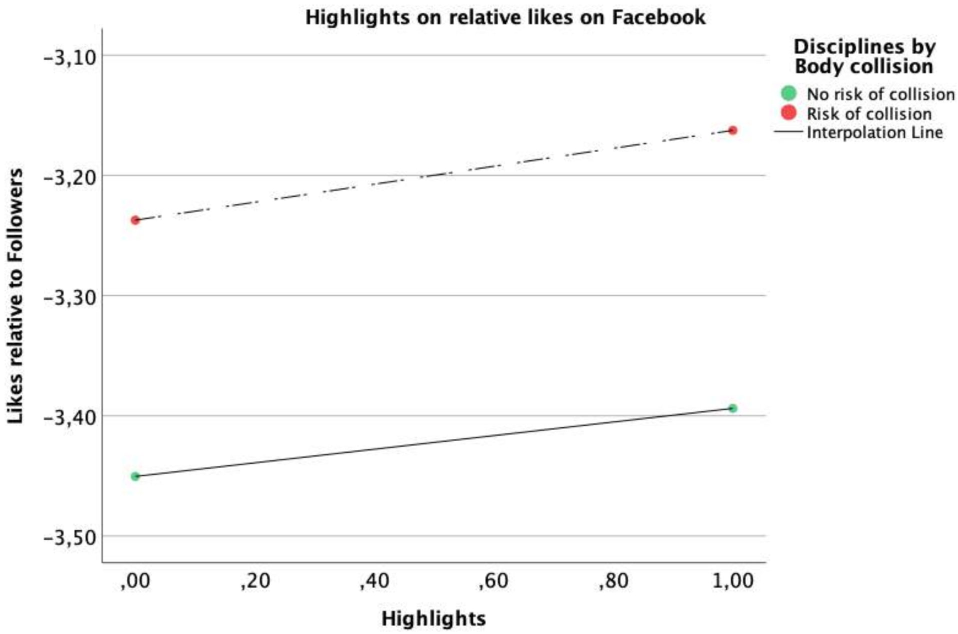


Fig. 93 Impact of *Hooking* on *relative likes* on Facebook

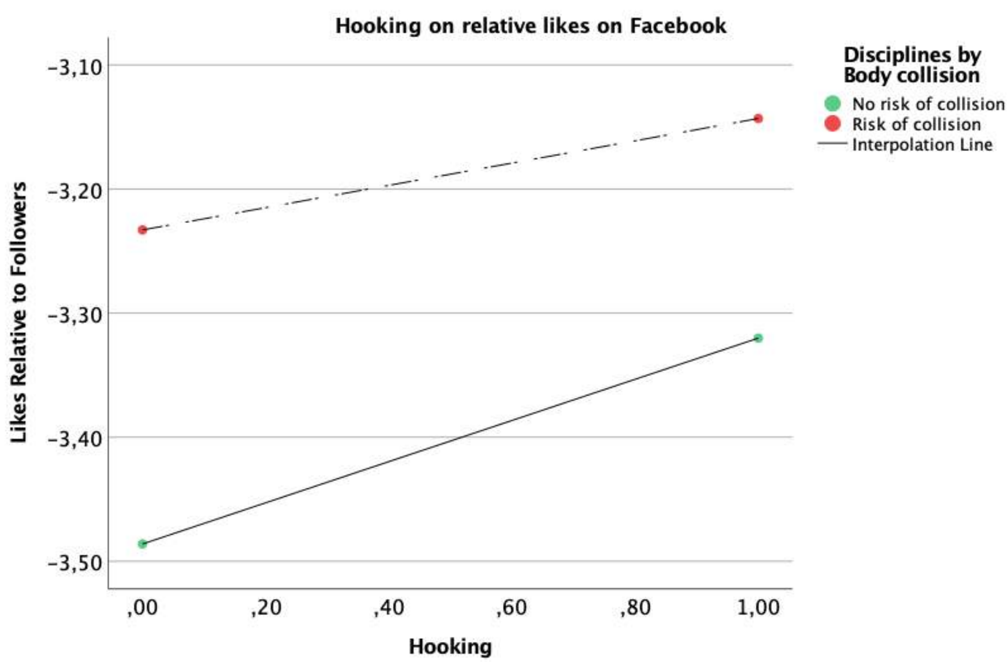


Fig. 94 Impact of *News* on *relative likes* on Facebook

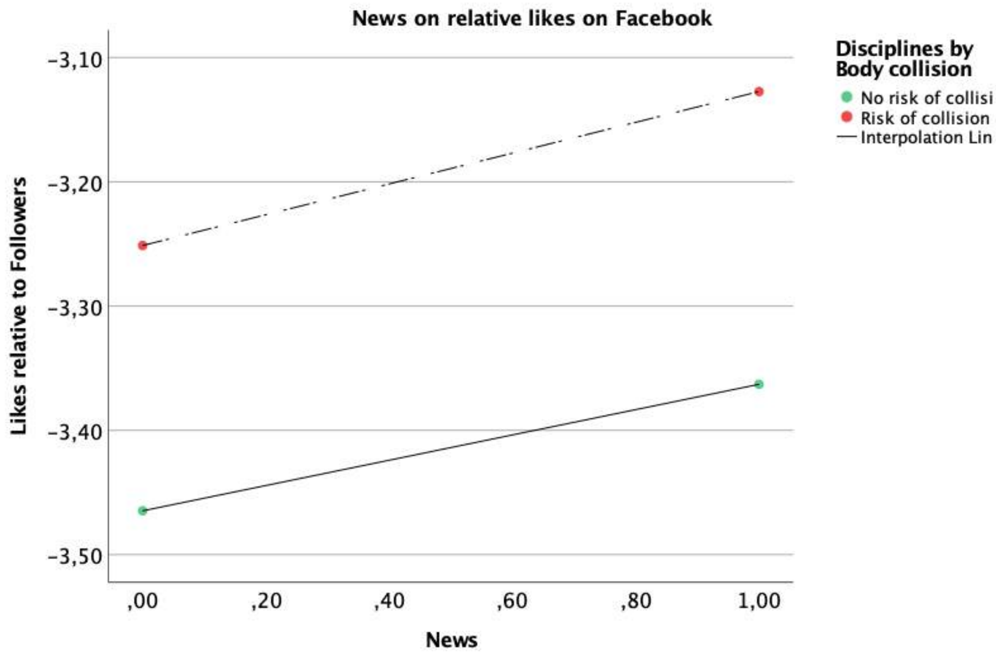


Fig. 95 Impact of *News* on *relative comments* on Facebook

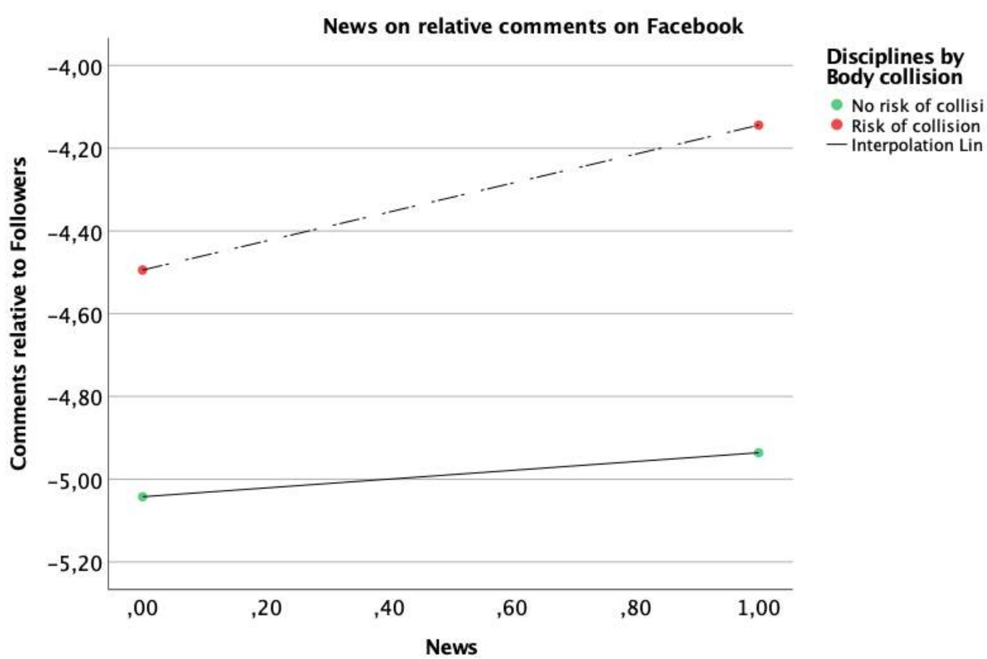


Fig. 96 Impact of *Gallery* on *relative comments* on Facebook

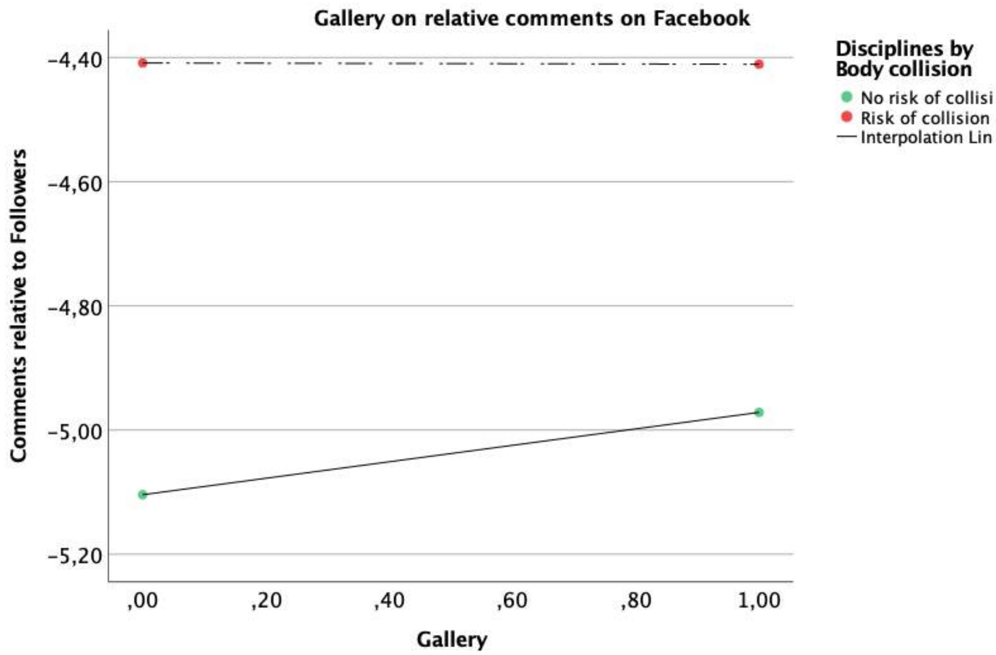


Fig. 97 Impact of *Gallery* on absolute comments on Facebook

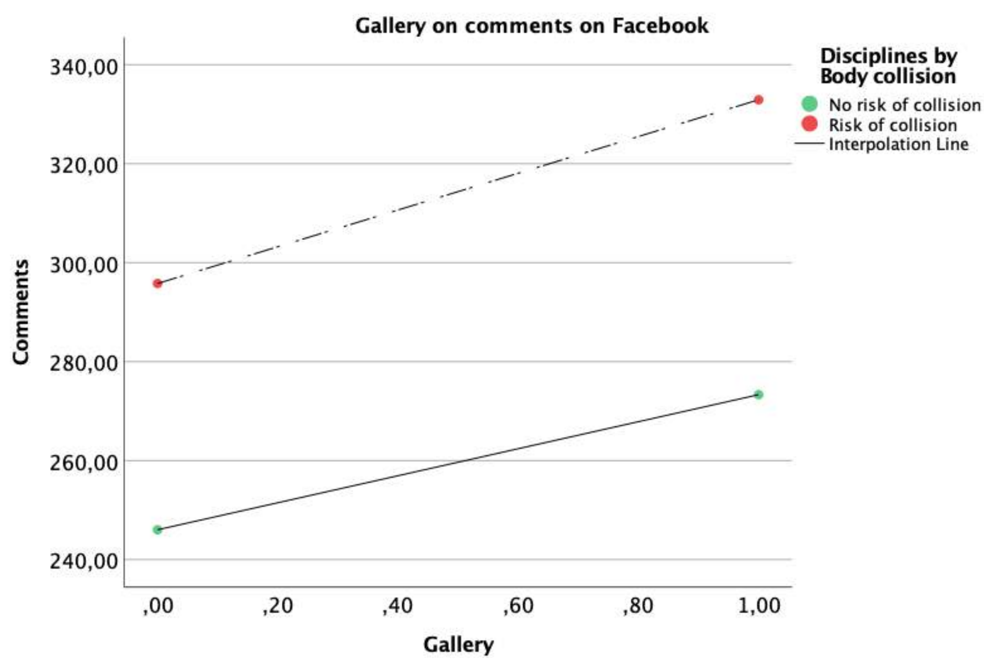


Fig. 98 Impact of *Gallery* on *relative likes* on Facebook

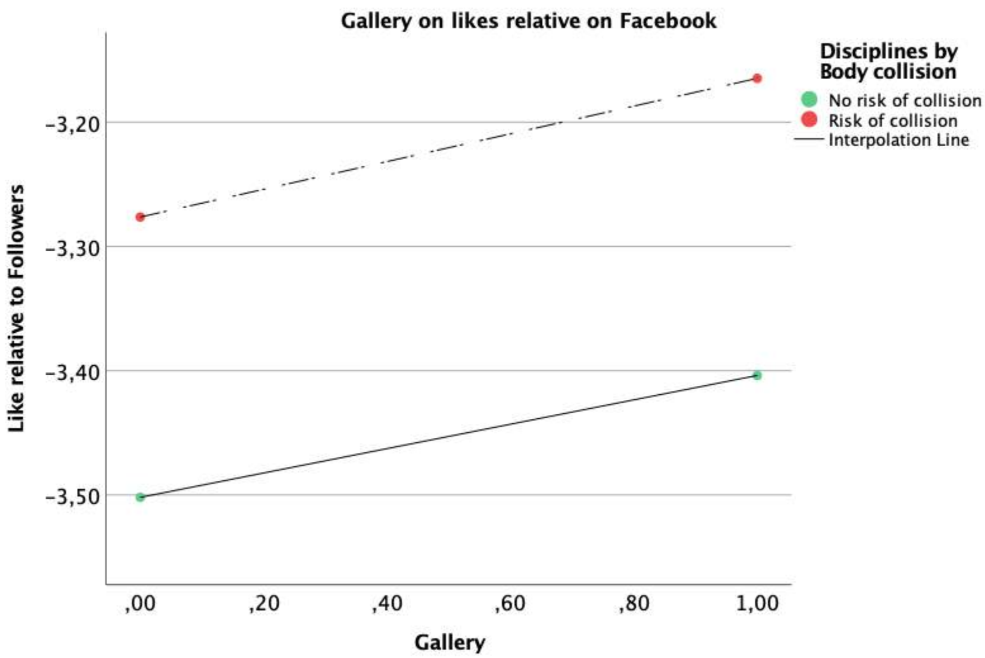
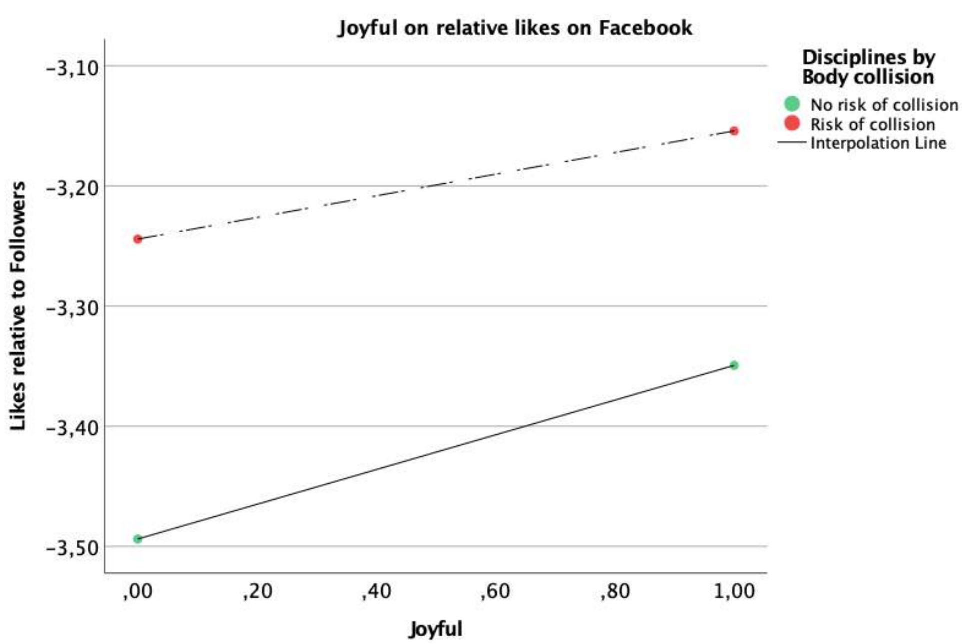


Fig. 99 Impact of *Joyful* on *relative likes* on Facebook



In the following three subdimensions, the relationship goes in the same direction, but its strength significantly varies from group to group. Posting content that presents the *Development*, training or recruitment of a team or players has a decreasing effect on *relative comments* and *likes* for both *collision* and collision free sports. Publishing *Statistics* also decreases the number of *relative likes* (in a much more pronounced way in *collision* sports) among all sports categories.

Fig. 100 Impact of *Development* on *relative likes* on Facebook

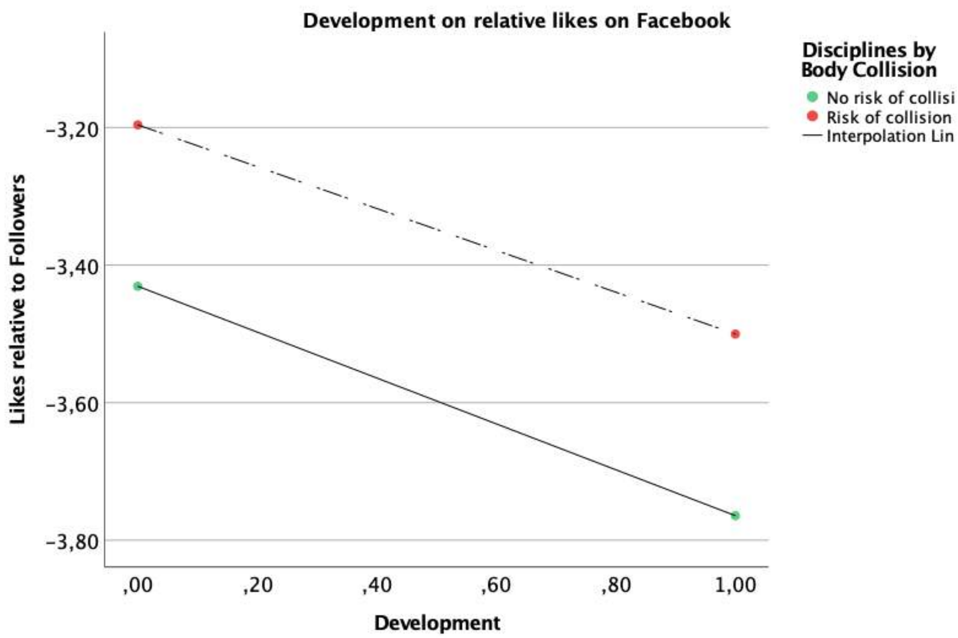


Fig. 101 Impact of *Development* on *relative comments* on Facebook

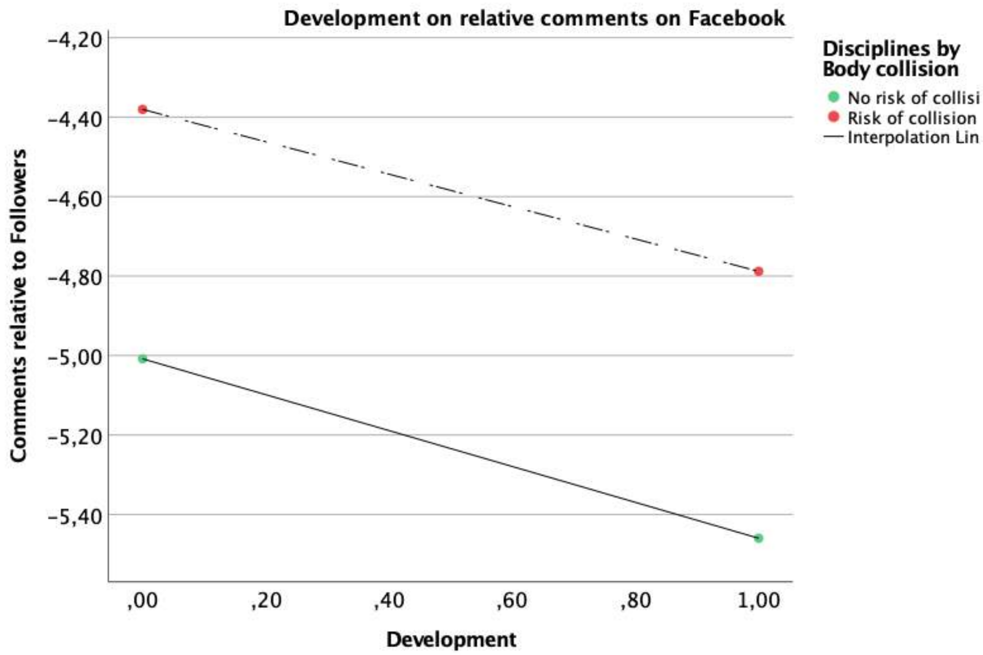


Fig. 102 Impact of *Statistics* on *relative likes* on Facebook

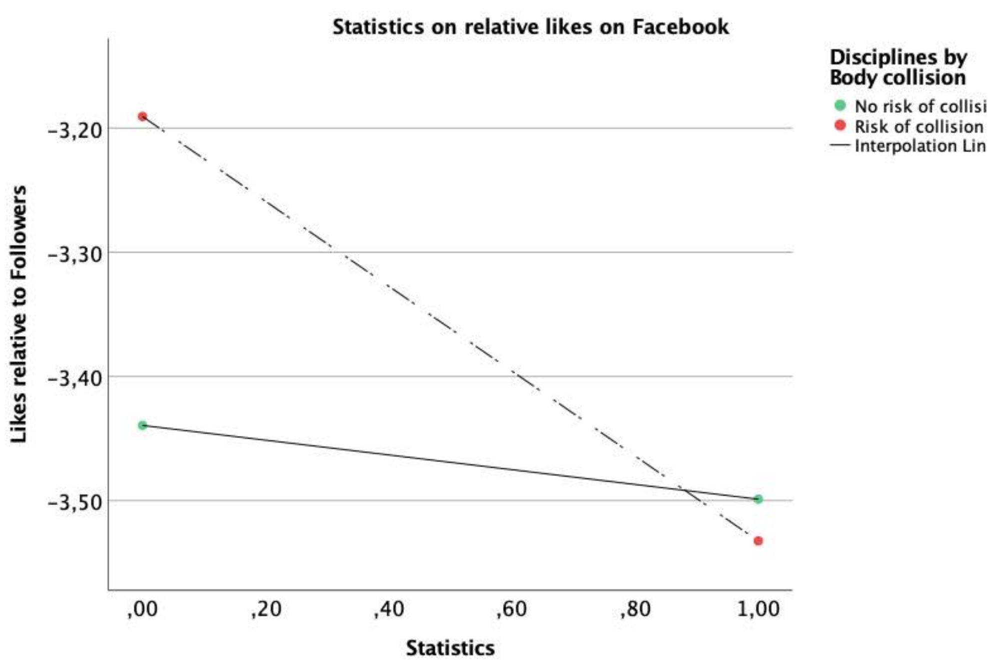


Table 42 *Social* subdimensions on *likes* on Facebook

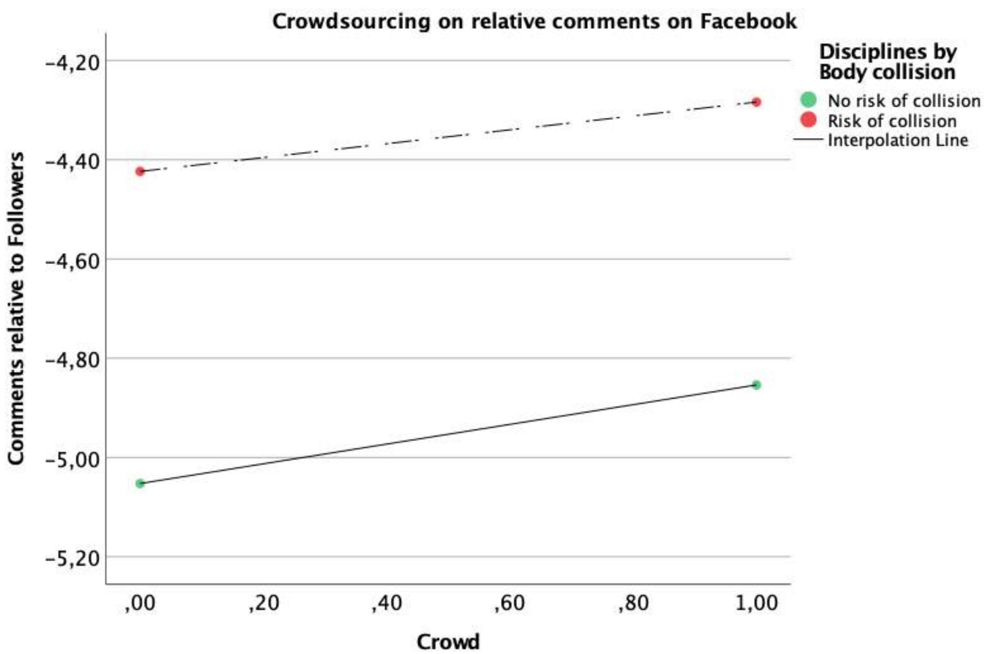
Social subdimensions	β	se	*t*	*p*	R^2
Bonding	-0.05	0.05	-1.08	0.28	
bodycoll * Bonding	0.17	0.07	2.36	**0.02**	0.12
Evangelization	0.45	0.4	1.11	0.27	
bodycoll *Evangelization					
Defending	0.05	0.13	0.4	0.69	
bodycoll *Defending	0.1	0.17	0.6	0.55	0.12
Social Spotlight	0.52	0.25	2.07	**0.04**	
bodycoll *Social Spotlight	0.52	0.25	2.07	**0.04**	0.12
Small Talk	-0.15	0.13	-1.22	0.22	
bodycoll *Small Talk	-0.03	0.19	-0.13	0.9	0.12
Intimacy	-0.07	0.05	-1.35	0.18	
bodycoll *Intimacy	0.06	0.07	0.86	0.39	0.12
Behind-the-scenes	-0.13	0.04	-3.17	**0.00**	
bodycoll * *Behind-the-scenes*	0.04	0.06	0.66	0.51	0.12
Crowdsourcing	-0.06	0.05	-1.17	0.24	
bodycoll *Crowdsourcing	0.08	0.09	0.93	0.35	0.12
Charity	-0.09	0.09	-1.01	0.31	
bodycoll *Charity	0.11	0.12	0.96	0.34	0.12
N	1,449				
Mean	-3.32				
Standard Deviation	0.6				

Table 43 *Social* subdimensions on *comments* on Facebook

Social subdimensions	β	se	*t*	*p*	R^2
Bonding	-0.1	0.06	-1.82	0.07	
bodycoll * Bonding	0.27	0.09	2.89	**0.00**	0.11
Evangelization	1.44	0.52	2.75	**0.01**	
bodycoll *Evangelization					
Defending	0.24	0.17	1.45	0.15	
bodycoll *Defending	0.63	0.22	2.84	**0.01**	0.11
Social Spotlight	0.28	0.33	0.84	0.4	
bodycoll *Social Spotlight	0.279	0.331	0.844	0.4	0.1
Small Talk	-0.11	0.16	-0.67	0.51	
bodycoll *Small Talk	0.06	0.25	0.22	0.82	0.1
Intimacy	-0.1	0.06	-1.58	0.12	
bodycoll *Intimacy	0.11	0.1	1.16	0.25	0.1
Behind-the-scenes	-0.23	0.05	-4.51	**0.00**	
bodycoll * *Behind-the-scenes*	0.09	0.07	1.2	0.23	0.1
Crowdsourcing	0.13	0.06	2.06	**0.04**	
bodycoll *Crowdsourcing	0.55	0.12	4.75	**0.00**	0.11
Charity	-0.31	0.11	-2.78	**0.01**	
bodycoll *Charity	-0.01	0.16	-0.09	0.93	0.1
N	1,546				
Mean	-4.68				
Standard Deviation	0.78				

Crowdsourcing increases the number of *relative comments* on Facebook for all sports followers.

Fig. 103 Impact of *Crowdsourcing* on *relative comments* on Facebook



Bonding decreases the number of *relative comments* in all types of sports. In collision-free sports, bonding decreases likes. In collision sports, bonding doesn't reduce the number of likes, but rather increases them very slightly, it's hardly noticeable, as the curve borders on the zero.

Fig. 104 Impact of *Bonding* on *relative comments* on Facebook

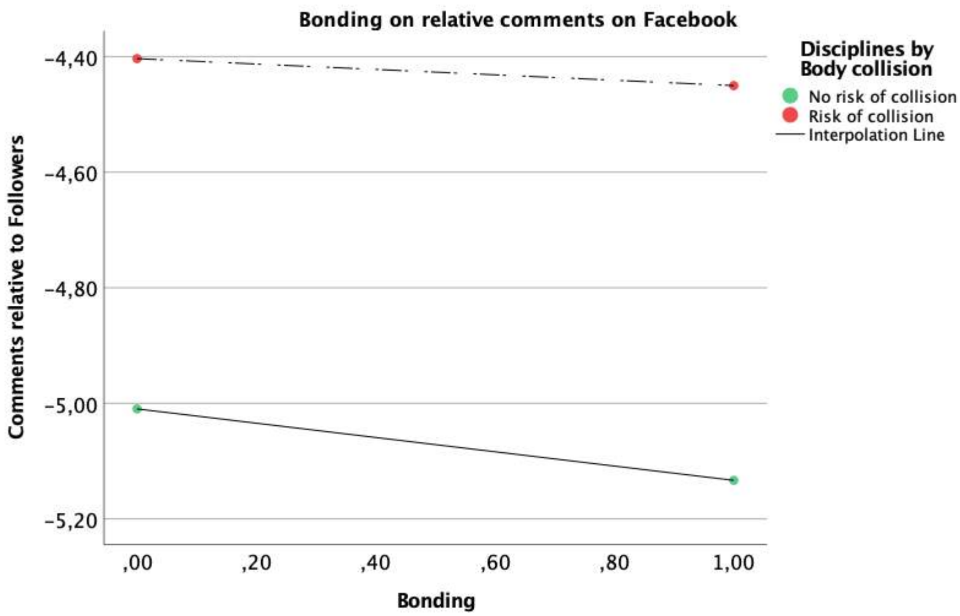


Fig. 105 Impact of *Bonding* on *relative likes* on Facebook

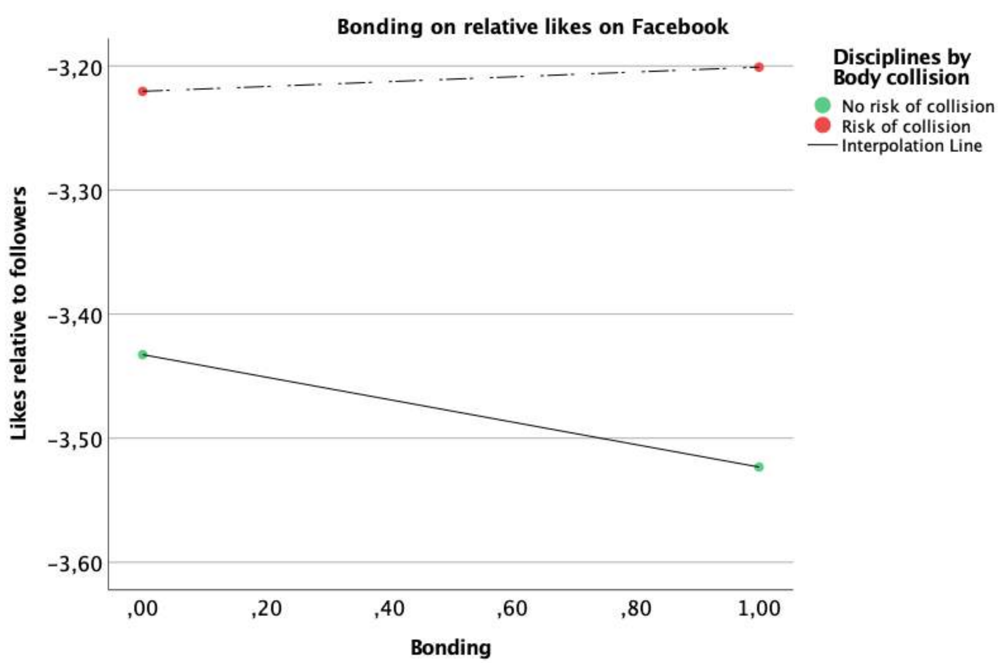
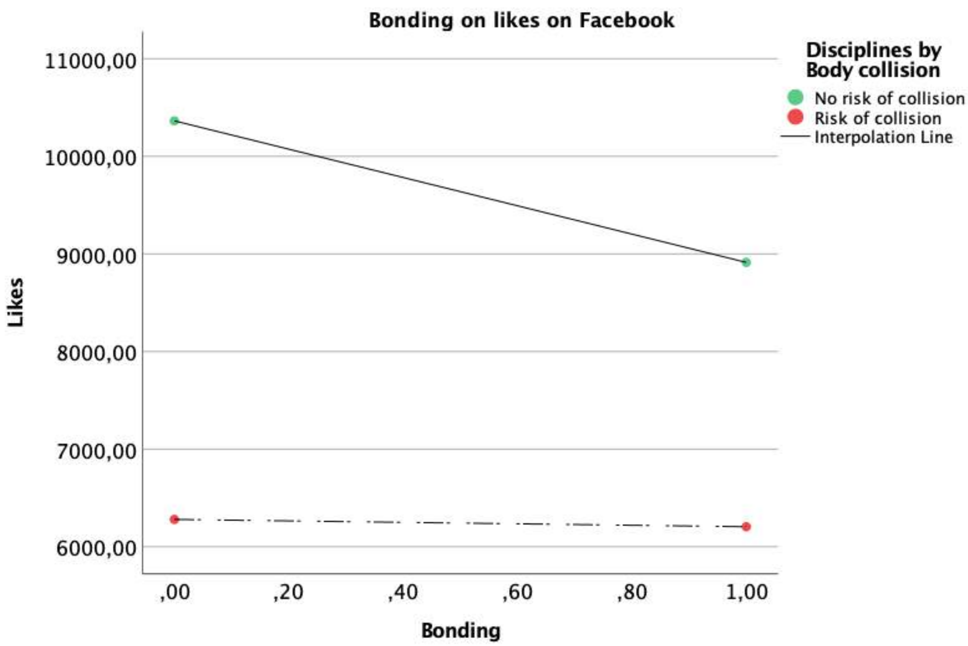


Fig. 106 Impact of *Bonding* on *likes* on Facebook



The effect of *Defending* significantly depends on *body collision*. As *Defending* increases, *relative comments* increase in *body collision* sports and decrease in non-collision sports.

Fig. 107 Impact of *Defending* on *relative comments* on Facebook

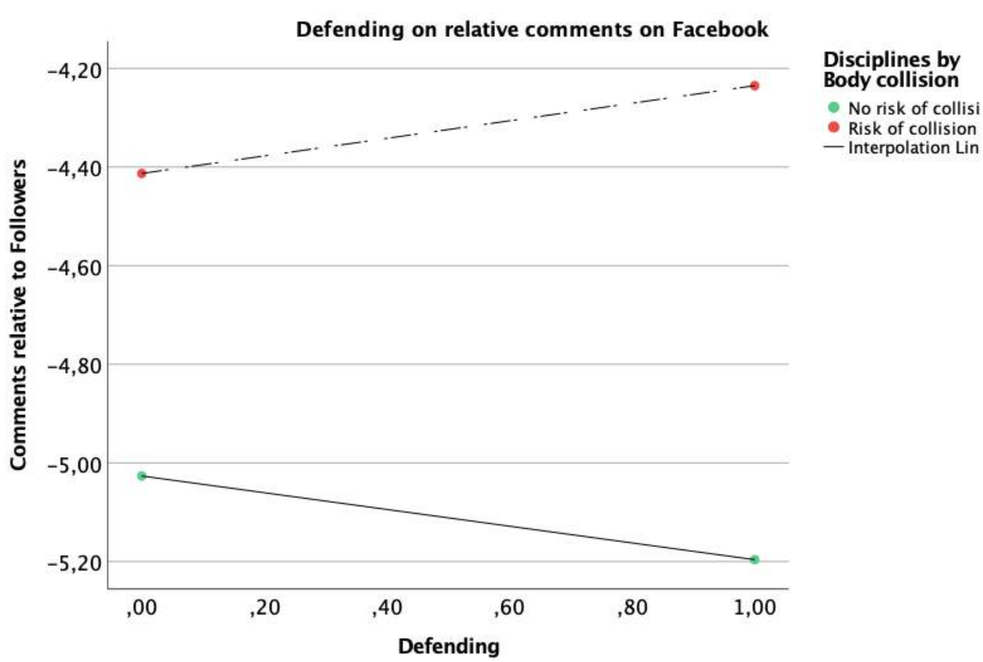


Table 44 *Selling* subdimensions on *likes* on Instagram

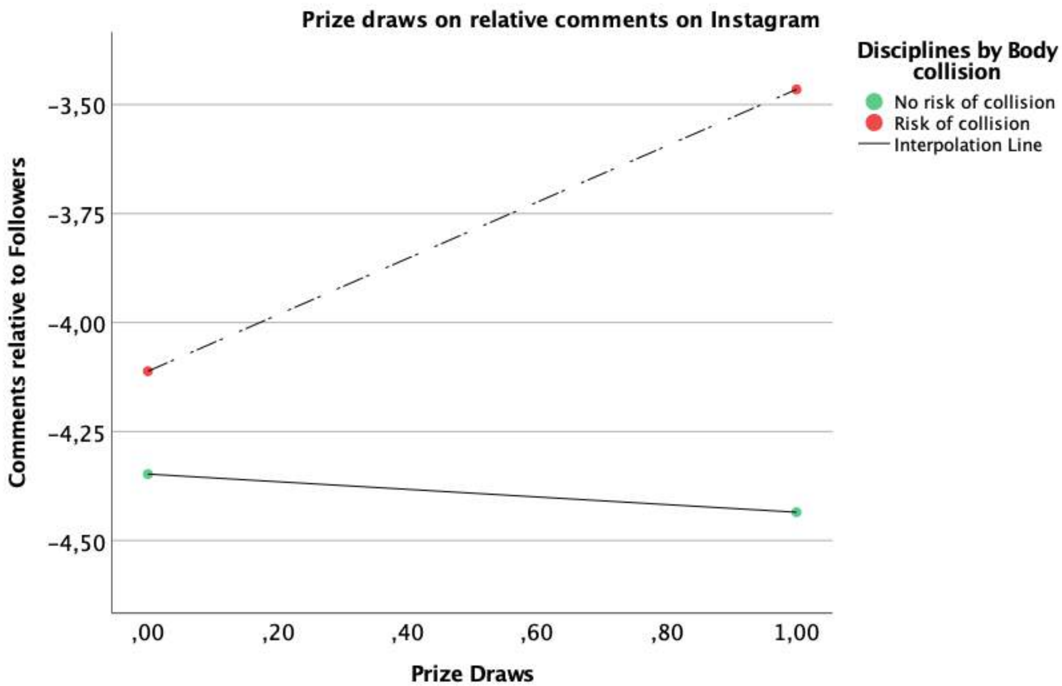
Selling subdimension	β	se	*t*	*p*	R^2
Explicit selling	0.03	0.13	0.23	0.82	
bodycoll*Explicit	0.15	0.17	0.91	0.36	0.2
Implicit selling	-0.09	0.02	-4.18	**0.00**	
bodycoll*Implicit	-0.05	0.03	-1.92	0.06	0.2
Product	0.05	0.06	0.84	0.4	
bodycoll*Product	0.13	0.09	1.44	0.15	0.2
Price					
bodycoll*Price					
Subscrip	-0.01	0.14	-0.07	0.94	
bodycoll*Suscrip	0.04	0.15	0.25	0.81	0.2
EventMarketing	0.03	0.11	0.29	0.78	
bodycoll*EventM	-0.1	0.17	-0.59	0.56	0.2
EventsTickets	-0.07	0.02	-3.1	**0.00**	
bodycoll*EventT	-0.07	0.03	-2.27	**0.02**	0.2
PrizeDraws	0.02	0.12	0.2	0.84	
bodycoll*PrizeDraws	0.14	0.19	0.74	0.46	0.2
CrossPromo	-0.12	0.03	-4.12	**0.00**	
bodycoll * Cross	-0.04	0.04	-1.08	0.28	0.2
Mean					
Standard Deviation					
N					

Table 45 *Selling* subdimensions on *comments* on Instagram

Selling subdimension	β	se	*t*	*p*	R^2
Explicit selling	-0.04	0.2	-0.18	0.85	
bodycoll*Explicit	0.04	0.25	0.17	0.87	0.14
Implicit selling	-0.06	0.03	-1.87	0.06	
bodycoll*Implicit	0.01	0.04	0.17	0.86	0.14
Product	-0.11	0.1	-1.14	0.25	
bodycoll*Product	-0.12	0.13	-0.87	0.38	0.14
Price					
bodycoll*Price					
Subscrip	-0.05	0.21	-0.24	0.81	
bodycoll*Suscrip	0.04	0.23	0.16	0.87	0.14
EventMarketing	0.16	0.16	0.99	0.32	
bodycoll*EventM	-0.21	0.25	-0.82	0.41	0.14
EventsTickets	-0.06	0.04	-1.71	0.09	
bodycoll*EventT	-0.02	0.05	-0.37	0.72	0.14
PrizeDraws	0.28	0.17	1.63	0.1	
bodycoll*PrizeDraws	1.03	0.28	3.72	**0.00**	0.15
CrossPromo	-0.05	0.04	-1.12	0.26	
bodycoll * Cross	0.02	0.06	0.35	0.73	0.14
Mean					
Standard Deviation					
N					

The effect of *Prize Draws* on comments depends on whether the sport has a risk of *collision* or not. In *collision* sports *Prize Draws* increase comments.

Fig. 108 Impact of *Prize Draws* on *relative comments* on Instagram



Selling Tickets and *Events* lowers the number of likes among followers of *collision* sports as well as those of collision free sports. For non-collision sports, the curves before and after the Log transformation are sharp. Since the Log10 deemphasizes outliers, the discrepancy between them indicates that a few of the event and ticket sales publications have a sharp deviation downward from the mean, sufficient to drive down engagement levels significantly.

Fig. 109 *Events Tickets* on *relative likes* on Instagram

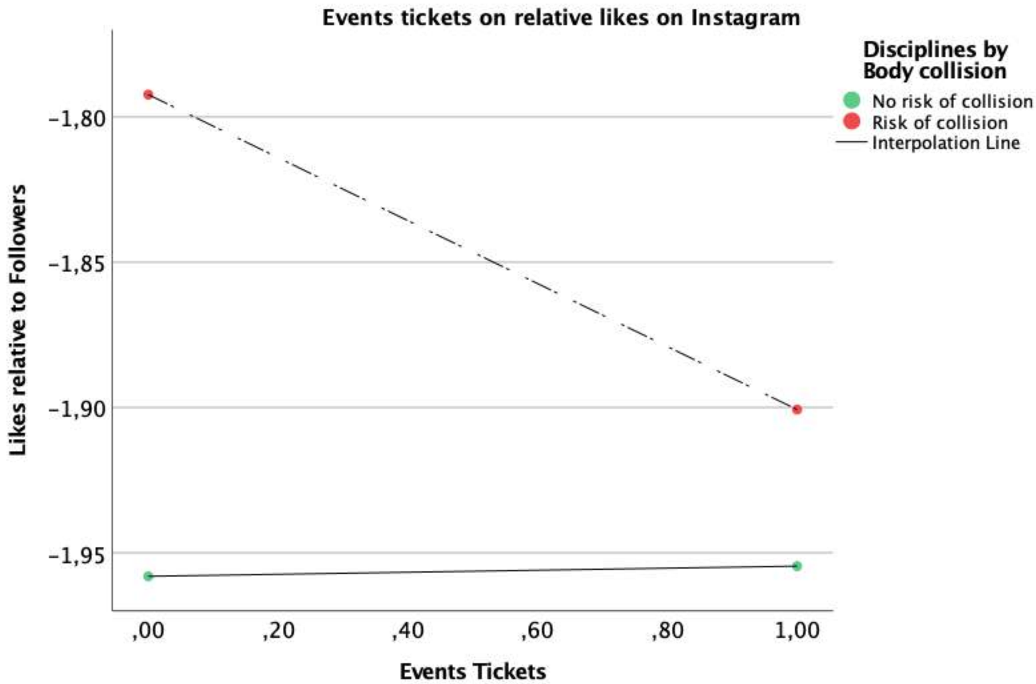


Fig. 110 Events tickets on *absolute likes* on Instagram

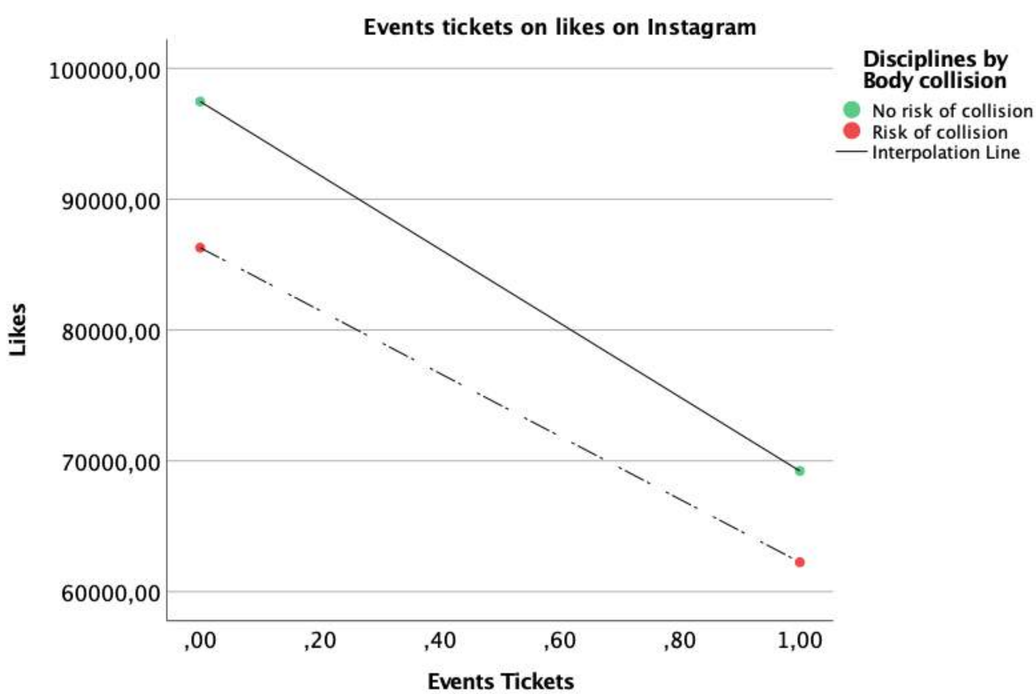


Table 46 *Quality* subdimensions on *likes* on Instagram

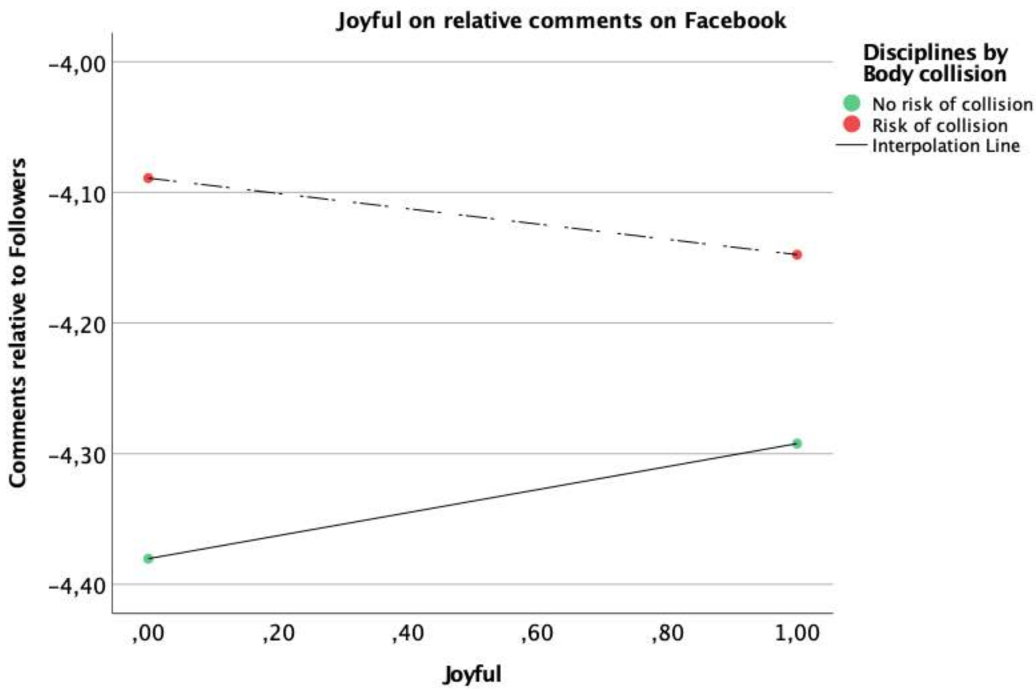
Quality subdimensions	β	se	*t*	*p*	R^2
Production process	-0.09	0.27	-0.35	0.73	
bodycoll * Production	-0.094	0.267	-0.351	0.73	0.2
Development	-0.04	0.04	-1.06	0.29	
bodycoll *Development	-0.06	0.07	-0.81	0.42	0.2
Hooking	0.02	0.02	0.74	0.46	
bodycoll *Hooking	0.12	0.04	3.38	**0.00**	0.2
Stats	-0.09	0.04	-2.1	**0.04**	
bodycoll *Stats	0.04	0.07	0.57	0.57	0.2
Immersion	-0.13	0.06	-2.17	**0.03**	
bodycoll *Immersion	-0.224	0.1	-2.27	**0.02**	0.2
Bridging	-0.09	0.05	-1.85	0.06	
bodycoll *Bridging	-0.01	0.07	-0.08	0.93	0.2
Bridging People	0.05	0.07	0.72	0.47	
bodycoll *Bridging People	0.02	0.09	0.27	0.79	0.2
Healthy					
bodycoll *Healthy					
Joyful	0.03	0.02	1.59	0.11	
bodycoll *Joyful	0.12	0.03	4.81	**0**	0.21
News	0.01	0.03	0.41	0.68	
bodycoll *News	0.04	0.03	1.36	0.17	0.2
Gallery	-0.02	0.02	-0.89	0.37	
bodycoll *Gallery	0.12	0.02	5.4	**0**	0.21
Highlights	-0.08	0.03	-2.73	**0.01**	
bodycoll *Highlights	-0.02	0.04	-0.41	0.69	0.2
N	1,745				
Mean	-1.87				
Standard Deviation	0.42				

Table 47 *Quality* subdimensions on *comments* on Instagram

Quality subdimensions	β	se	*t*	*p*	R^2
Production process	-0.06	0.39	-0.15	0.88	
bodycoll * Production	-0.06	0.39	-0.15	0.88	0.14
Development	-0.08	0.06	-1.26	0.21	
bodycoll *Development	-0.07	0.1	-0.67	0.5	0.14
Hooking	0.03	0.04	0.91	0.36	
bodycoll *Hooking	0.16	0.05	3.17	**0.00**	0.14
Stats	-0.11	0.06	-1.7	0.09	
bodycoll *Stats	0.13	0.1	1.33	0.19	0.13
Immersion	-0.2	0.08	-2.37	**0.02**	
bodycoll *Immersion	-0.27	0.14	-1.89	0.06	0.14
Bridging	-0.06	0.07	-0.9	0.37	
bodycoll *Bridging	0.07	0.1	0.67	0.5	0.14
Bridging People	0.03	0.1	0.32	0.75	
bodycoll *Bridging People	0.02	0.13	0.17	0.86	0.14
Healthy					
bodycoll *Healthy					
Joyful	0	0.03	-0.12	0.9	
bodycoll *Joyful	0.1	0.04	2.68	**0.01**	0.14
News	0.13	0.04	3.5	**0.00**	
bodycoll *News	0.26	0.05	5.44	**0.00**	0.15
Gallery	-0.1	0.03	-3.57	**0.00**	
bodycoll *Gallery	0.13	0.03	3.99	**0.00**	0.15
Highlights	-0.2	0.04	-5.04	**0.00**	
bodycoll *Highlights	-0.07	0.06	-1.16	0.25	0.14
N	1,740				
Mean	-4.2				
Standard Deviation	0.59				

The direction of the effect of *Joyful* on *relative comments* depends on whether the sport has a risk of *collision* or not. As seen below, in *collision* sports *Joyful* decreases comments, whereas in non-collision sports it increases them.

Fig. 111 *Joyful* on *relative comments* on Instagram



The *body collision* moderator alters the strength of the relation between the predictors below on their corresponding outcomes. Some subdimensions increase specific engagement measures, regardless of the risk of *collision* such as *Joyful* (on *relative likes*), *News* (on *relative comments*), *Hooking* (on likes and *relative comments*). Some decrease engagement on all types of sports such as *Gallery* (on *relative likes* and *relative comments*) and *Immersion* (on *relative likes*).

Fig. 112 *Joyful* on *relative likes* on Instagram

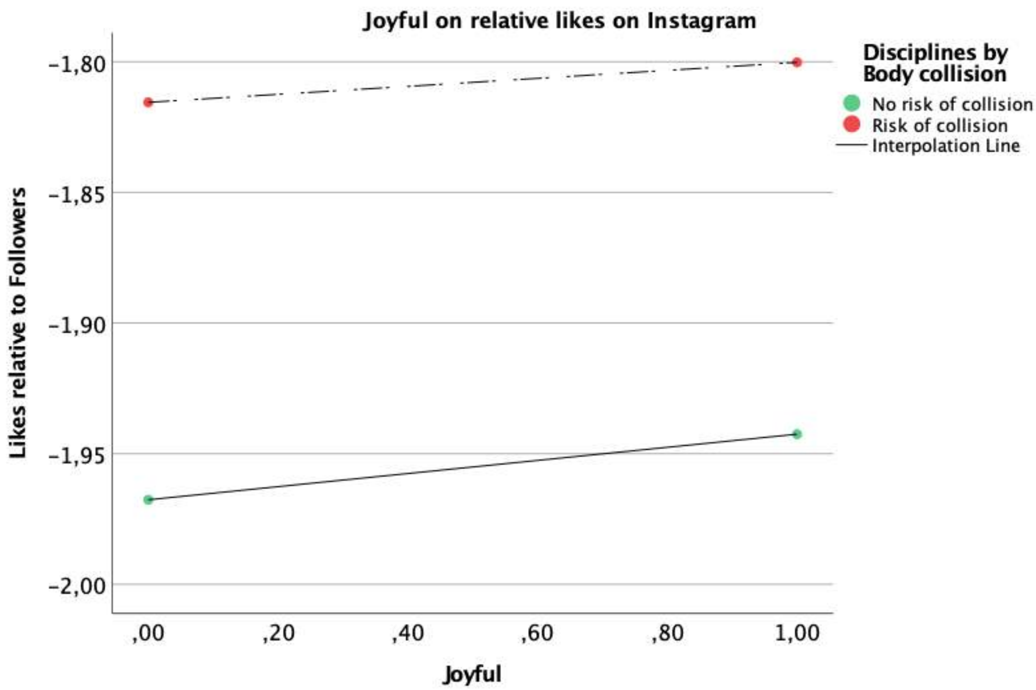


Fig. 113 *News* on *relative comments* on Instagram

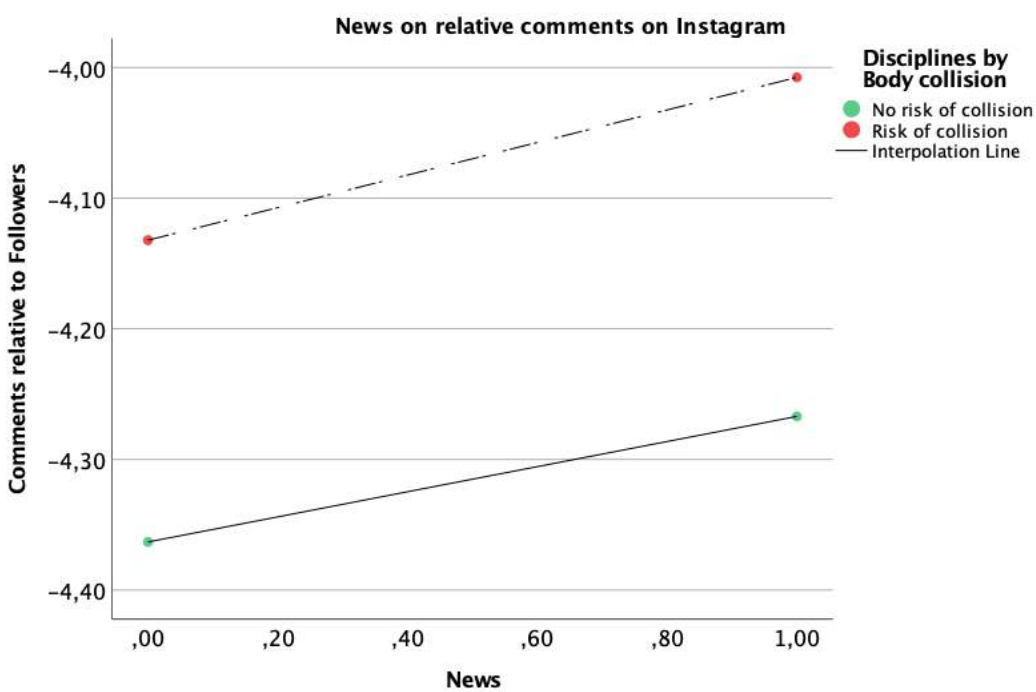


Fig. 114 *Hooking* on *relative likes* on Instagram

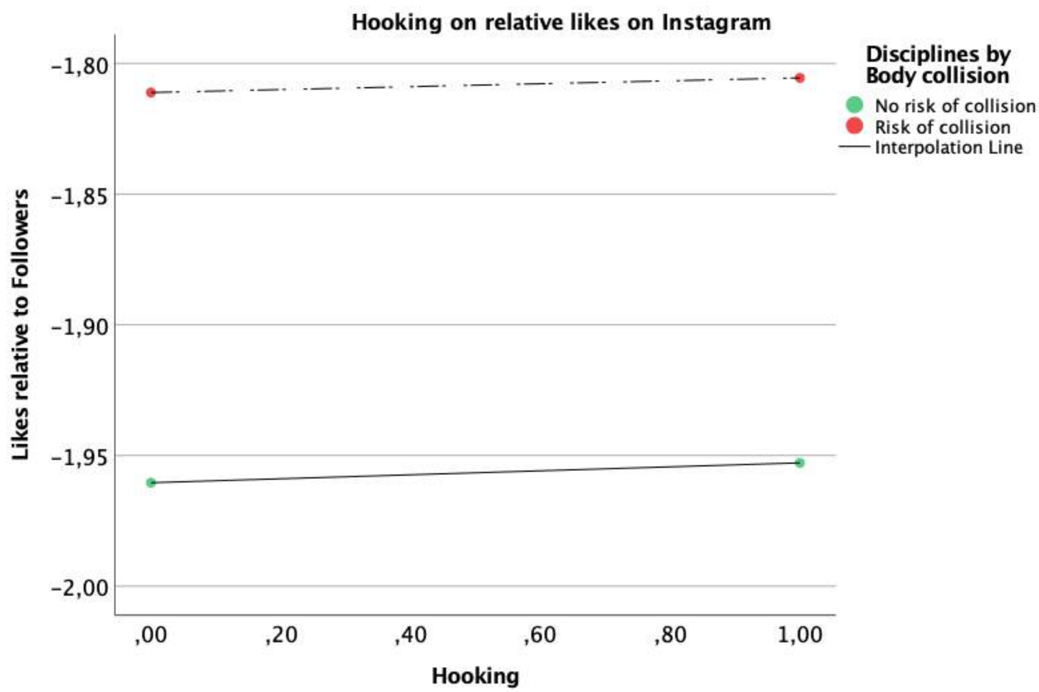


Fig. 115 *Hooking* on *absolute likes* on Instagram

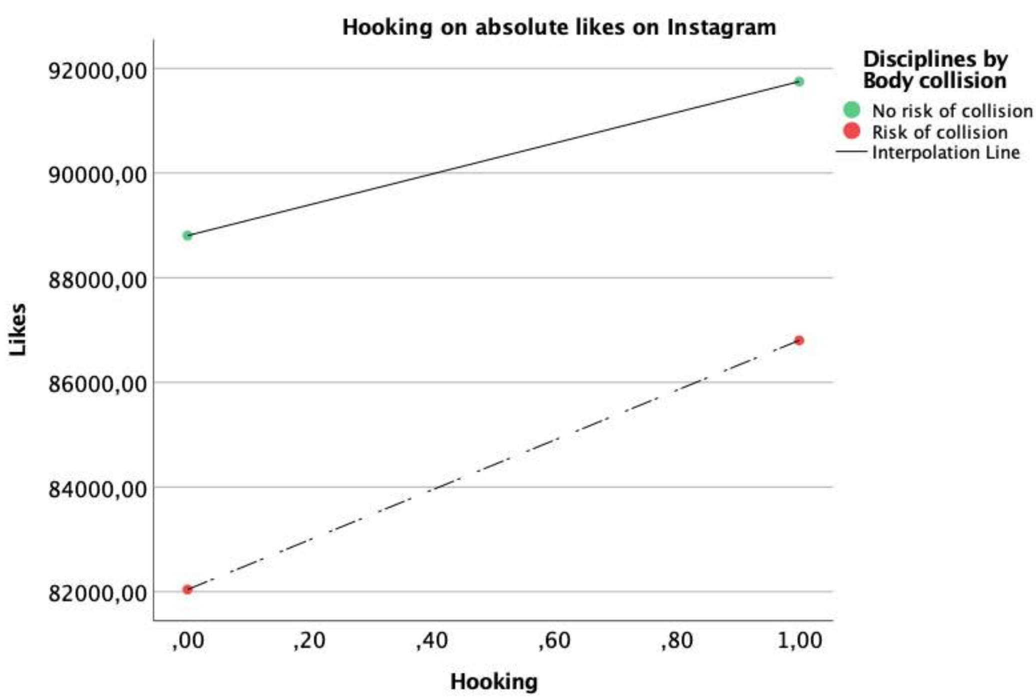


Fig. 116 *Hooking* on *relative comments* on Instagram

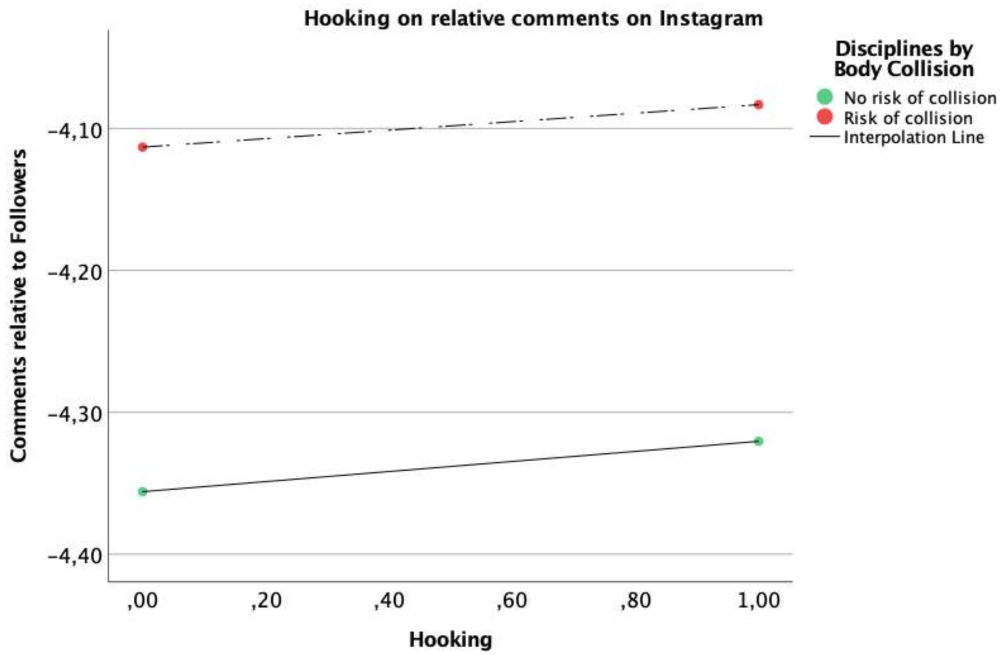


Fig. 117 *Gallery* on *relative likes* on Instagram

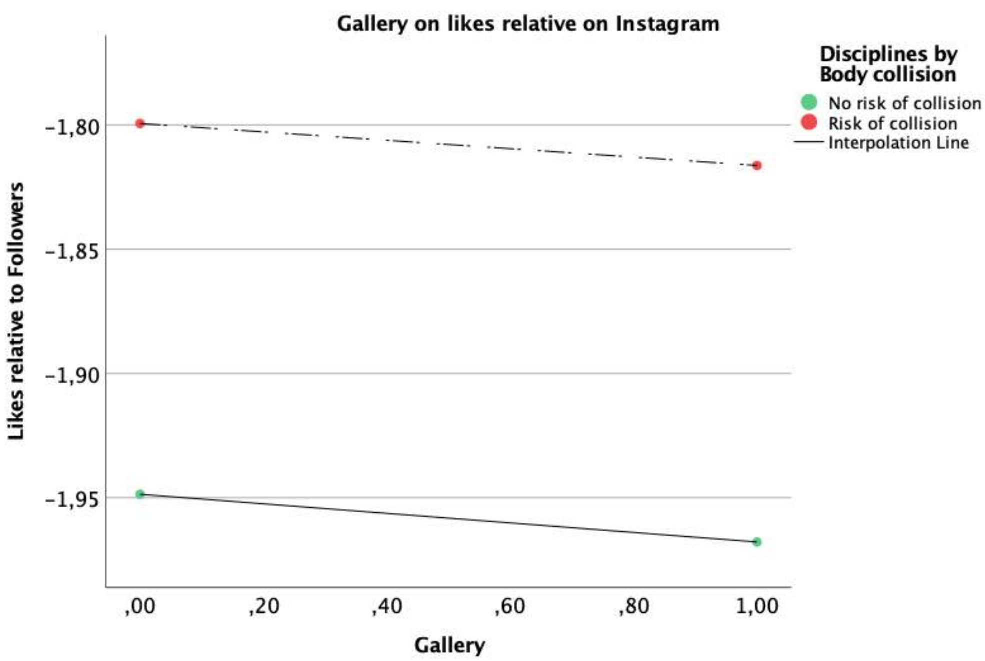


Fig. 118 *Gallery* on *relative comments* on Instagram

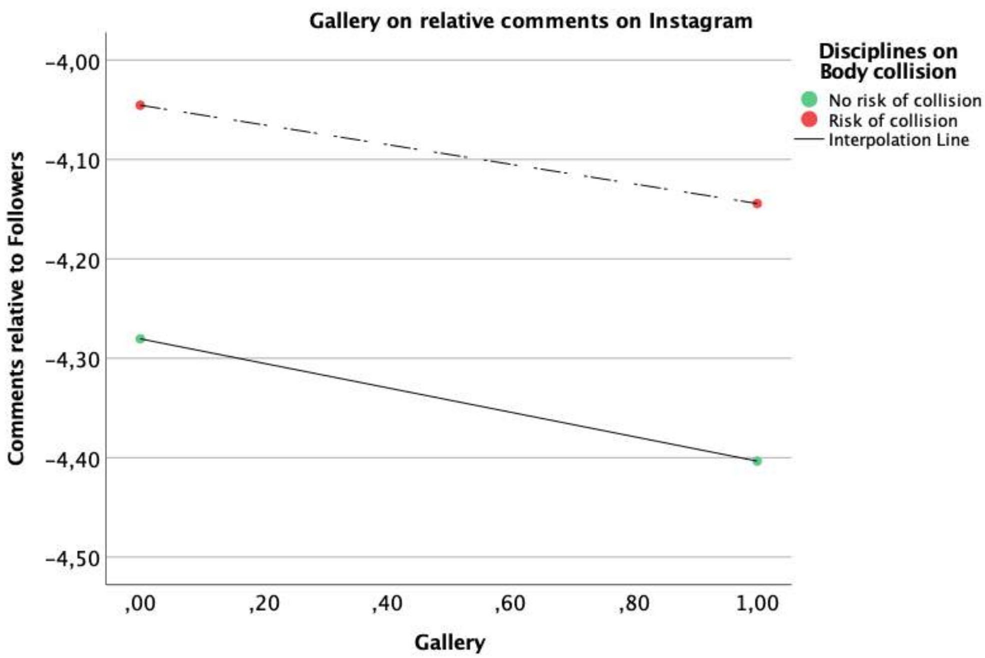


Fig. 119 *Immersion* on *relative likes* on Instagram

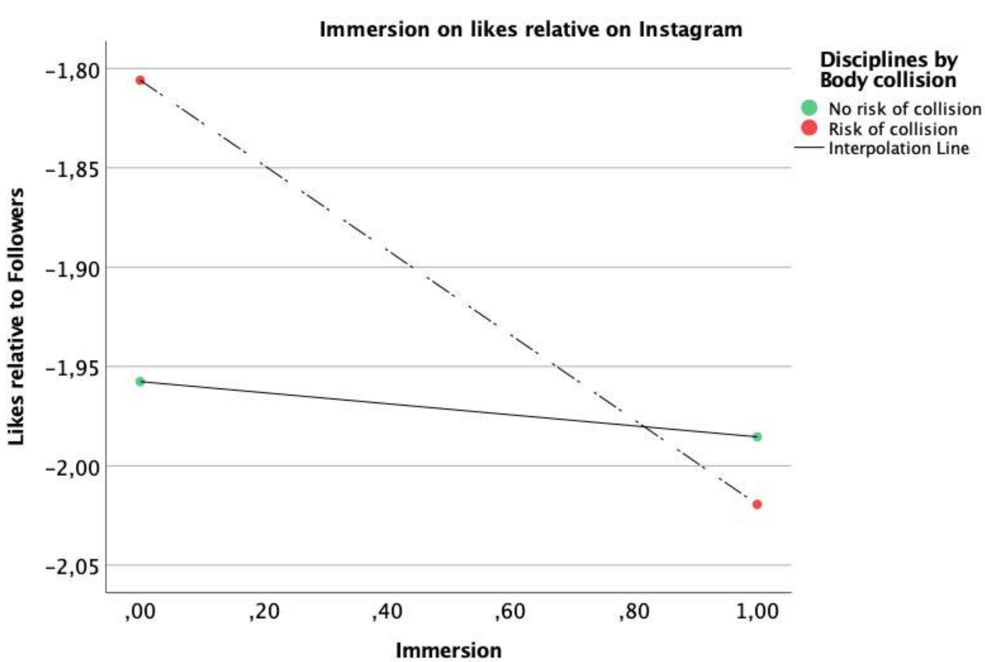


Table 48 *Social* subdimensions on *likes* on Instagram

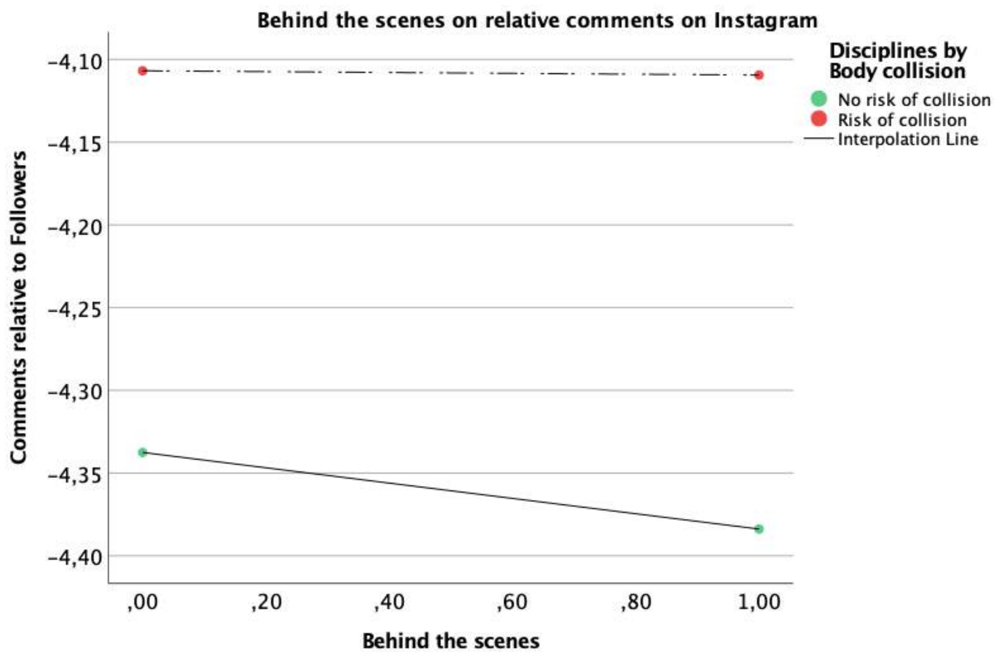
Social subdimensions	β	se	*t*	*p*	R^2
Bonding	0.06	0.03	2.36	**0.02**	
bodycoll * Bonding	0.09	0.04	2.40	**0.02**	0.20
Evangelization	0.20	0.38	0.54	0.59	
bodycoll *Evangelization	0.20	0.38	0.54	0.59	0.20
Defending	0.00	0.07	-0.05	0.96	
bodycoll *Defending	0.08	0.11	0.72	0.47	0.20
Social Spotlight	-0.10	0.13	-0.75	0.45	
bodycoll *Social Spotlight	-0.07	0.17	-0.43	0.67	0.20
Small Talk	-0.13	0.08	-1.73	0.08	
bodycoll *Small Talk	-0.01	0.11	-0.13	0.90	0.19
Intimacy	-0.06	0.03	-1.92	0.06	
bodycoll *Intimacy	0.02	0.05	0.52	0.61	0.20
Behind-the-scenes	0.03	0.02	1.45	0.15	
bodycoll * *Behind-the-scenes*	0.14	0.03	5.42	**0.00**	0.21
Crowdsourcing	0.05	0.03	1.78	0.08	
bodycoll *Crowdsourcing	0.11	0.05	2.30	**0.02**	0.20
Charity	-0.22	0.06	-3.45	**0.00**	
bodycoll *Charity	-0.08	0.12	-0.65	0.51	0.19
N	1,747				
Mean	-1.87				
Standard Deviation	0.42				

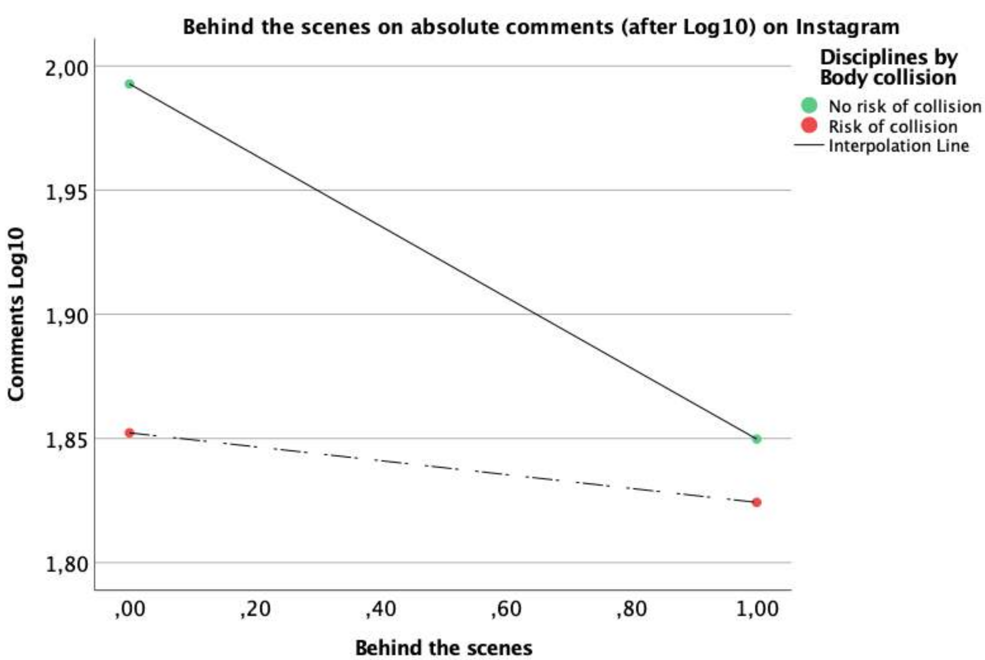
Table 49 *Social* subdimensions on comments on Instagram

Social subdimensions	β	se	*t*	*p*	R^2
Bonding	0.16	0.04	4.28	**0.00**	
bodycoll * Bonding	0.17	0.06	3.08	**0.00**	0.14
Evangelization	1.68	0.55	3.05	**0.00**	
bodycoll *Evangelization	1.68	0.55	3.05	**0.00**	0.14
Defending	-0.15	0.10	-1.41	0.16	
bodycoll *Defending	-0.13	0.16	-0.79	0.43	0.13
Social Spotlight	0.02	0.21	0.10	0.92	
bodycoll *Social Spotlight	0.14	0.25	0.55	0.59	0.13
Small Talk	-0.16	0.11	-1.46	0.15	
bodycoll *Small Talk	0.04	0.16	0.25	0.80	0.13
Intimacy	-0.07	0.05	-1.48	0.14	
bodycoll *Intimacy	0.02	0.07	0.34	0.73	0.13
Behind-the-scenes	-0.02	0.03	-0.62	0.53	
bodycoll * *Behind-the-scenes*	0.15	0.04	3.69	**0.00**	0.14
Crowdsourcing	0.36	0.04	8.33	**0.00**	
bodycoll *Crowdsourcing	0.35	0.07	5.02	**0.00**	0.15
Charity	-0.25	0.10	-2.67	**0.01**	
bodycoll *Charity	0.02	0.18	0.11	0.91	0.13
N	1,742				
Mean	-4.20				
Standard Deviation	0.59				

Body collision alters the strength of the relation between *Behind-the-scenes* content, and both *likes* and *comments relative* to followers. For *collision* sports as well as those without collision, backstage content lowers the number of comments.

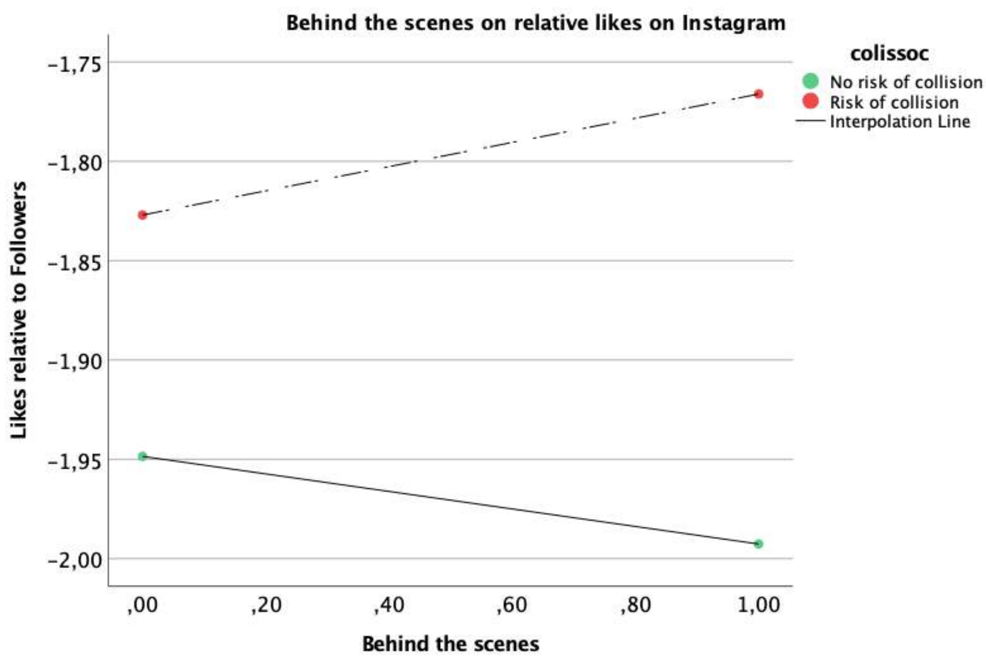
Fig. 120 *Behind-the-scenes* on *relative comments* on Instagram





In the examples below, the two groups are opposed. The direction of the effect depends on whether the sport has a risk of *collision* or not. In *collision* sports, *Behind-the-scenes* content increases *relative likes* whereas in non-collision sports it decreases them.

Fig. 121 *Behind-the-scenes* on *relative likes* on Instagram



In *non-collision* sports, *Bonding* and *Crowdsourcing* contents increase *relative likes* whereas in *collision* sports they decrease them. However, they have an increasing influence on the number of *relative comments* among both groups.

Fig. 122 *Bonding* on *relative likes* on Instagram

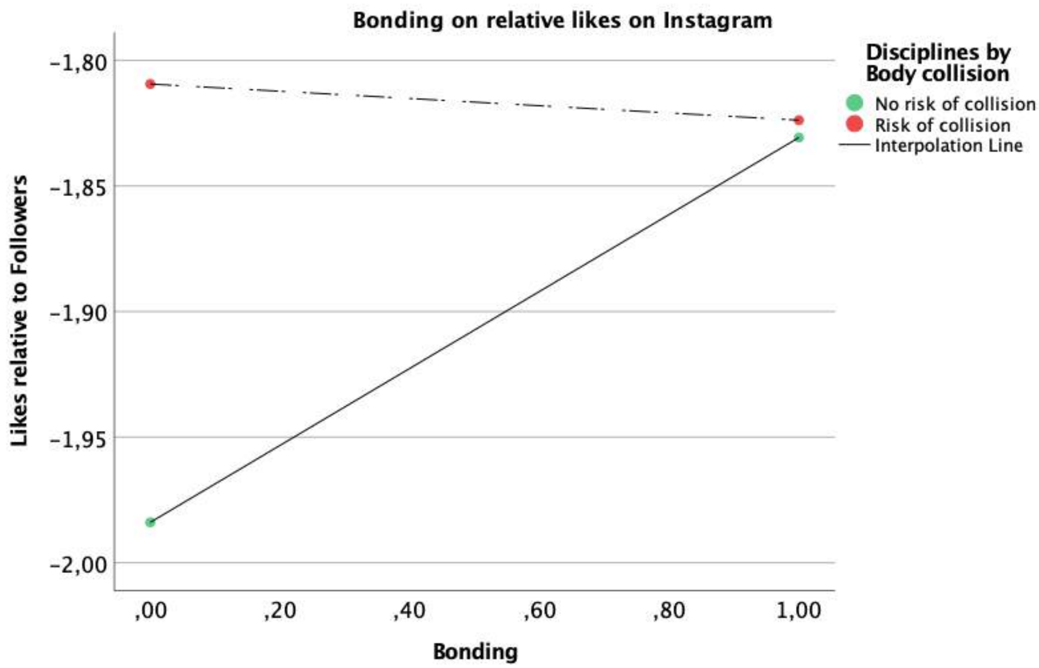


Fig. 123 *Crowdsourcing* on *relative likes* on Instagram

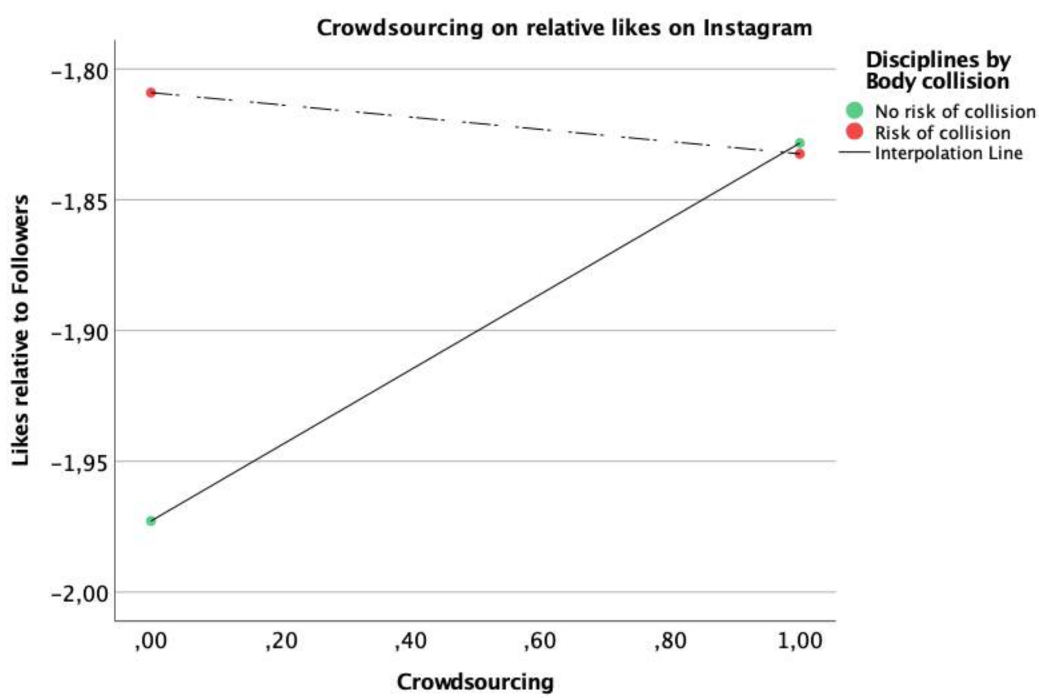


Fig. 124 *Bonding* on *relative comments* on Instagram

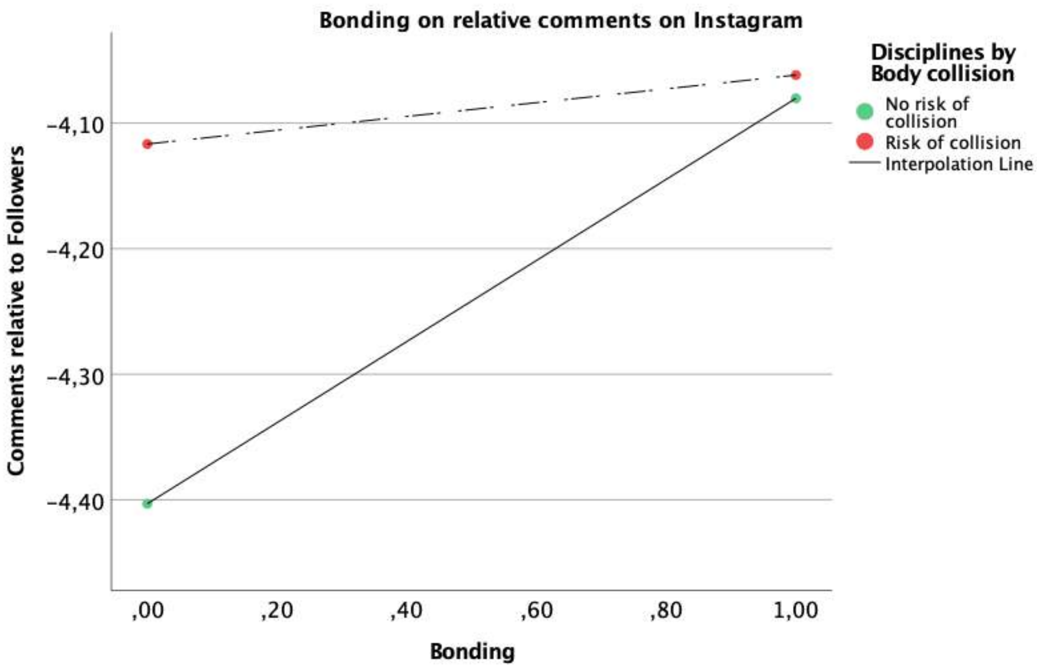
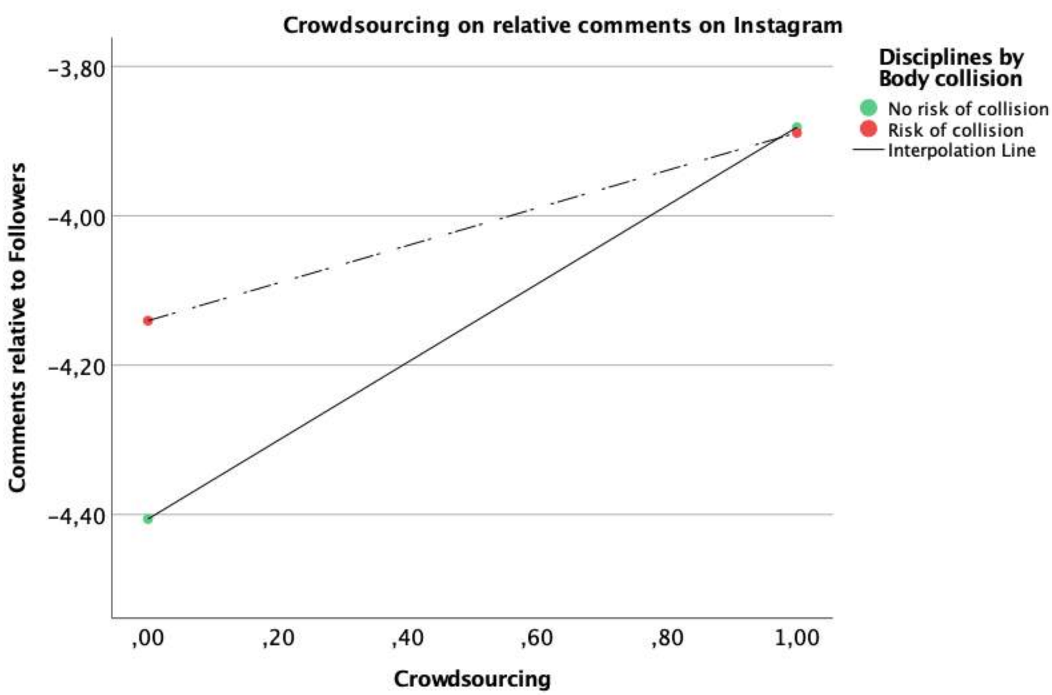


Fig. 125 *Crowdsourcing* on *relative comments* on Instagram



Following these analyses, it is possible to answer the question ***: "Are some subdimensions of content associated differently from what was observed in the content dimension level ?"*** The association between content subdimensions, CE and SNS differed from those observed at the content dimension level. **On Twitter,** like the *selling* dimension, *selling* subdimensions lower consumer engagement. *Collision* sports followers have more tolerance to certain *selling* contents such as *Implicit Selling*, *Product Promotion*, *Prize Draws* and *Cross-Promotions*. *Quality* increases engagement on Twitter. For *collision* sports followers, *Hooking*, *Bridging*, *Joyful*, *News* and *Gallery* contents have an increasing influence on engagement. In non-collision sports, the direction of these relationships varies. Only *Hooking* content has an increasing influence on all followers and all metrics. Across Twitter, if *social* initially seemed to show little or no effect on followers' engagement, it increases likes for *collision* sports and reduces likes for non-collision sports. Similarly, *Crowdsourcing* and *Bonding* increase engagement in *collision* sports and decrease comments in non-collision sports. On **Facebook**, like the overall *selling* dimension, there are six *selling* subdimensions which have a significant effect on users' engagement, namely *Explicit Selling*, *Implicit Selling*, *Product/Family Promotion*, *Price*, selling of *Events* and *Tickets* and *Cross-Promotions*. Scatter plots of two subdimensions pre and post Log10 are in reverse. Among *collision* sports followers, the *Explicit Selling* (on comments) and the *Cross-Promotion* (on likes) before transformation reduce engagement, while after transformation these increase engagement. In de-emphasizing outliers, the mid-values become much less overpowered by the extreme values. Returning to the original data, we conclude that the two subdimensions reduce engagement. However, it is worthwhile mentioning that by placing less emphasis on the extremes, these *selling* subdimensions among collision sports followers can increase engagement.

Regarding *quality*, the hypothesis put forward in question 2 is much too simplistic, as it does not unilaterally increase comments in collision-free sports and decrease them in *collision* sports. While some subdimensions reflect that statement (*Hooking, Highlights* and *Joyful*), they also increase likes in both categories. *News* and *Gallery* increase engagement among all followers and on all metrics. *Development* and *Statistics* decrease engagement regardless of the level of *body collision*. As for *social*, results indicated that it had a decreasing effect on both likes and comments. If *Bonding* follows that general rule, *Crowdsourcing* however breaks the pattern, increasing the number of comments in all types of sports followers. **On Instagram,** the *selling* dimension has a decreasing effect on likes and comments. When measured in likes, collision-free sports have a higher tolerance to *selling* content. Among *collision* sports enthusiasts, *Prize Draws* increase engagement (in comments). *Quality* has an overall decreasing effect on the number of comments made by users. There are some subdimensions which have an increasing effect on engagement. Regardless of whether they are *collision* sports or not, breaking *News* increases comments while *Hooking* boosts both comments and likes. As far as *Joyful* goes, it increases both measures as well, but only in non-collision sports. *Immersion* reduces likes and *Gallery* reduces likes and comments for all types of sports.

As for *social,* among collision-free sports followers, *Crowdsourcing* and *Bonding* increase engagement (in likes and comments). *Behind-the-scenes* decreases engagement (likes and comments). In *collision* sports, the picture is less clear. For each of these three dimensions, when likes increase, comments decrease and vice versa. To see all results at a glance, refer to Appendix F *Summary table of all results.*

This chapter began by introducing the various statistical tests that were to be discussed and the order in which they would be discussed. Followed by an overview of the sample's descriptive statistics and average engagement rates on the three SNS. Then, we addressed each of the four research questions. The findings of the first research question showed *quality* to be the most widely use content dimension on Twitter, Facebook and Instagram among sports organizations. They use it throughout all their SNS in more than 85 % of posts. The results of question two indicate that the choice of SNS moderates the relationship between the content and the engagement of online consumers. *Selling* decreases engagement on all social networks with varying degrees of intensity. *Quality*, on the other hand, has an impact that varies not just in intensity, but also on the direction of the relationship. *Social* also has an impact that varies in intensity and direction. Question three reveals that not all sports followers are affected by content in the same way. *Collision* disciplines garner on average 25 % more likes and comments per post than those from non-collision sports. By separating collision and non-collision sports, several trends emerge, opposite of each other. Lastly, in answering our final research question, we learned that several of the subdimensions are not following the trend of the main dimension, which is an interesting and even salutary direction for managerial recommendations. Also, as our dimensions are constructs of Nepomuceno et al. (2020), it is challenging to find equivalents in the literature. Paralleling existing literature with subdimensions is much easier to do. The next chapter will present and analyze our interpretation of the results.

Chapter 5- Summary, Discussion and Conclusions

In the prior chapter, a presentation and analysis of the findings were made. Chapter 5 consists of a thesis summary, a discussion of the results, practical implications, and recommendations for future research as well as conclusions.

The goal of these final sections is to elaborate further on the concepts studied to better grasp how the different content types generated by firms impact consumer engagement across social networking sites and to present some suggestions for additional research to further increase these levels of engagement. Lastly, a summary is offered to capture both the essence and scope of the research that has been attempted in this study.

5.1 Summary

The purpose of the study was to measure the impacts of three distinct content dimensions : (1) the *selling* dimension, (2) the *quality* dimension, and (3) the *social* dimension on consumer engagement (measured in the number of *relative likes* and *relative comments*) while comparing them across three major social networks used by sports organizations, i.e., Twitter, Facebook, and Instagram, through qualitative hand-coding and quantitative analysis.

The dimensions and subdimensions of content from the study by Nepomuceno and al. (2020) were revisited and adapted to the study context. A total of 5,000 publications scraped on the official Twitter, Facebook and Instagram social media accounts belonging to 233 various Sports Organizations were hand coded by two students in marketing, under the guidance of Professor Nepomuceno, using a binary system (1 = belongs to the category, 0 = does not belong to the category), until an interrelated reliability score of 99 % or greater was achieved. To assess the validity of the constructs (*architecture*, *selling*, *quality*, and s*ocial*), the formative model was chosen over the reflective model, as the dimensions are composite measures, in which each item is unique, and none are interchangeable.

This study included four research questions:

1. *What dimension of content do sports companies predominantly use on their official social networks ?*
2. *To what extent are the different dimensions of content generated by sports organizations associated with consumers' engagement on their official social networking sites ?*
3. *How does the risk of body collision in sport impact the relationship between the content dimensions of the FGC and the CE ?*
4. *To what extent are the different subdimensions of content generated by sports organizations associated with consumers' engagement on their official SNS ? How does the risk of body collision in sport impact the relationship between the content subdimensions of the FGC and the CE ?*

To answer question 1, a simple univariate analysis, descriptive statistics output in SPSS, was sufficient. To answer question 2, several linear regressions were run to measure the impact of *selling*, *quality* and *social* on consumer engagement, while keeping our control variables constant. We evaluated one platform at a time, using select cases. To answer questions 3 and 4, we performed multiple logistic regressions with the PROCESS modeling tool by Andrew F. Hayes v 3.5. (Haynes, 2021). For question 3, the effect of *selling*, *quality* and *social* on engagement was tested for each platform, adding this time the moderating effect - the addition of a third element that changes the nature of the relationship - of *body collision*. Question 4 goes further, as subdimensions become the predictors, rather than dimensions. This takes us from 18 regressions in question 3 to 180 separate regressions or 60/platform in question 4.

5.2 Discussion of the Findings

Previous researchers (Bai and Yan, 2020 ; Santiago and al., 2022 ; Yang and al., 2019) extensively studied firm generated content. The goal of our study is to measure the impact of different types of content on consumer engagement and compare them on Twitter, Facebook and Instagram. Then, to determine to what extent sports context changes the results by the types or sports followed. And finally, to identify the one-off posts that firms generate that have a significant effect on engagement. This section discusses the implications of the findings for each of the four research questions.

Research Question One

What dimension of content do sports companies predominantly use on their official social networks ?

The findings resulting from question one indicate that the content dimension most used by sports organizations is *quality*. Over 88 % of the 5,000 posts analyzed include the *quality* dimension. *Quality*-driven posts promote the brand's symbolic or hedonic characteristics (Nepomuceno and al., 2020 ; Tafesse and Wien, 2018). In sports, highlighting team and organizational *quality* is largely done through high-quality, artistic images and videos. 72 % of all the *quality* content posted by sports organizations (thus 63 % of all the content posted by them) is either the *Highlights* from the latest matches, i.e. winning plays, through videos and photographs or artistically captured high performances of players through photographs and videos (*Gallery*). Although the users and architectures are different, sports organizations publish approximately the same ratio of *quality* content to total content on each platform. Instagram, described as a space to pass the time, has a slightly higher ratio at 90 % versus 86 % on Facebook and 88 % on Twitter (Doyle and al., 2020 ; Voorveld and al., 2018).

In comparison, barely 40 % of posts have *social* content, focusing on establishing or maintaining consumer relationships (Ding and al., 2014 ; Kim and al., 2015). Although *the social* dimension was split in nine different categories, nearly 90 % of *social* content posted by the sports organizations falls in one of four areas : the *Behind-the-scenes* i.e. exclusive moments in between matches (34.5 % of all *social* posts) ; *Bonding* that develops a feeling of affiliation with the fans (21.5 % of *social* posts), *Intimacy* which generously discloses things about the team, league or players (13.9 % of all *social* posts), and *Crowdsourcing* which invites fans to contribute (19.6 % of *social* posts). Organizations are posting slightly more *social* content via Instagram – 47 % of all posts, versus 39 % on Facebook and 36 % on Twitter, nowhere near the 75 % ratio observed by Doyle and al. (2020) in their MLS study. *Social* content on Instagram leads to increased consumer engagement according to literature (Doyle and al., 2020 ; Nepomuceno and al., 2020 ; Subramani and Rajagopalan, 2003).

Finally, 33 % of the publications in our sample encourage *selling*, either implicitly or explicitly, which is rather low according to Kim and al. (2015) who state that one third to one half of all company publications consist of *selling*. Sports organizations post roughly 10 % more *selling* on Facebook than on their other networks in which nearly 40 % of all content posted contains *selling*. *Selling* on Facebook is a double-edged sword : some appreciated contents such as promoting events, giveaways, fun promotions, may increase the " like " factor in an exponential way, with one like being relayed to a peer an average of 130 times. Conversely, though, disliked *selling* contents decrease engagement and disengage followers (Coelho and al., 2016 ; Swani and al. (2013). By publishing more *selling* content through Facebook than through any of the other SNSs, organizations bank on their contents being appreciated.

Research Question Two

To what extent are the different dimensions of content generated by sports organizations associated with consumers' engagement on their official social networking sites ?

Findings in question two show some general trends : *selling* decreases engagement across all social networks ; *quality* increases engagement on both Twitter and Facebook yet decreases engagement on Instagram ; and, *social* has a decreasing or almost null effect on engagement. Most of these findings are consistent with the literature, though some authors do not agree with each other.

Across Facebook, consistent with previous research, we find that *selling* decreases engagement (Swani, 2013). Unlike Tafesse and Wien (2018) who find that *quality* is the strongest driver of engagement, our findings show that *quality* claims increase engagement only slightly and only on *relative likes*. Regarding *social*, while literature agrees on an effect ranging between nil to an increasing effect on engagement (Coelho and al., 2016 ; Pletikosa Cvijikj and al., 2013), we instead find it has a decreasing effect on engagement. This comes as no surprise as users state they use Facebook to entertain, document, stay in touch with friends and family, but never mention socialize or stay in touch with brands (Alhabash and al., 2017 ; Ding and al., 2014 ; Kepios, 2021 ; Quan-Haase and al., 2010 ; Raacke and al., 2008). By trying to increase engagement, the brands that intrude in these perceived as " intimate " social networks and attempt to establish relationships with their consumers risk instead diminishing their engagement.

Across Twitter, in line with past research results, we find that *selling* has a decreasing influence on engagement (Walker and al., 2021). Yet, *quality* increases engagement. Like Li and Xie (2020), we find that social networks moderate the *quality*-engagement relationship. For instance, on Twitter, where the textual contents have a dominant presence and visual contents are scarcer, the inclusion of a high-quality picture elicits higher levels of engagement, compared to Instagram which is a highly visual network. Lastly, in line with the literature consulted (Malhotra, 2012), *social* contents decrease the engagement slightly, in this instance in terms of *relative comments*.

Unsurprisingly, *selling* on **Instagram** shows a decreasing effect on engagement. Of the three SNSs, Instagram is most resistant to *selling* and concurrently is the network where organizations publish the least amount of *selling* contents (about 30.25 % of overall posts).

There is a consensus that both *quality* and *social* contents increase consumer engagement on Instagram (Ding and al, 2014 ; Doyle and al., 2020 ; Subramani and Rajagopalan, 2003 ; Nepomuceno and al., 2020). However, our results are not in line with past studies. We find that *quality* decreases *relative comments* and *social* does not significantly impact engagement. We find two possible explanations for these diverging results from the literature. Firstly, a fatigue effect : posting too much of the same contents results in overload (Bai and Yan., 2020 ; Nepomuceno and al, 2020). Indeed, organizations post more *quality* and *social* contents on Instagram than they do in their other platforms and further over-saturate their posts with more *quality* and *social* contents as well, that is, one post contains a greater amount of subdimensions. In posting this much *quality* contents, organizations overlook the fact that Instagram is an image-rich platform in which users are already overexposed to *quality* claims (Li and Xie, 2020 ; McAlexander and al., 2002). Secondly, contrary to Twitter and Facebook, there is an audience misfit. Instagram is predominantly frequented by women, only a third of whom are over the age of 34, whereas sports followers are 76 % male and mostly between the ages of 35-44 (Lange, 2020 ; Goug, 2022 ; Statistica, 2021).

Research Question Three

How does the risk of body collision in sport impact the relationship between the content dimensions of the FGC and the CE ?

The original research hypothesis was that the violence, rivalry, intensity and potential danger of collision between players and their surroundings increased spectators' enjoyment, interest and possibly engagement (Bryant and Zillmann, 1983 ; Mitchell and al., 1985). It is worthwhile mentioning that, on all three social networking sites, the average number of likes and comments for *collision* sports is greater than the average number of likes and comments for non-collision sports.

On Facebook, consistent with previous results, *selling* decreases engagement in both groups. However, *collision* sports' followers have a higher tolerance to *selling* (in *relative likes*). *Collision* sports fans are in a class of their own when it comes to the *quality* dimension. Unlike other sports followers, *quality* decreases comments among them.

On Twitter, consistent with previous results, *selling* has a decreasing effect on engagement. Again, *collision* sports have a better tolerance to *selling* (in *relative comments*). Contrary to other sports followers on Twitter, followers of *collision* sports welcome the *social* content as it increases likes among them.

On Instagram, the trend we previously observed reverses : *collision* sports' followers have a lower tolerance for *selling* than their comparables (in *relative likes*). After dividing the groups, a clear trend emerges, consistent with the literature, *social* contents increase *relative comments* regardless of the risk of bodily collision (Chandon, 1995 ; Coelho and al., 2016 ; Doyle and al., 2020 ; Subramani and Rajagopalan, 2003).

To wrap up, the findings from question three demonstrate very similar overall patterns to question two but add a few valuable insights for the firms. *Selling* decreases engagement across all social networks, but followers from different sports have different saturation points, breakpoints. On both Twitter and Facebook, *collision* sports have significantly higher *selling* tolerance. Additionally, *social* contents can increase engagement on Instagram when actions are examined and measured per sports category.

Research Question Four

To what extent are the different subdimensions of content generated by sports organizations associated with CE on their official SNS ? How does the risk of body collision in sport impact the relationship between the content subdimensions of the FGC and the CE ?

Across Facebook, five *selling* subdimensions decrease engagement, regardless of the sport followed. These are *Explicit Selling*, *Implicit Selling*, *Event/Ticket*, *Product/Family* and *Cross-Promotions*. The other four have no significant effect on consumer engagement.

As for *quality*, our initial findings showed that *quality* claims increase engagement only slightly. Most of the *quality* subdimensions increase consumer engagement, but not all of them. The following are the main ones. Publishing *Gallery* and *News* increase engagement on both metrics, for all sports followed. *Hooking*, *Joyful* and *Highlights* increase engagement nearly every time (apart from *relative comments* for *collision* sports). Finally*, Stats* and *Development* decrease engagement regardless of *collision* risk.

Though the findings from the second question indicated that *social* contents had a decreasing effect on engagement, the findings from the subdimensions are more nuanced. Firstly, while *Bonding* does decrease engagement across all measures, regardless of the risk of *collision*, it does show a modest increase on likes, amongst *collision* sports followers. Additionally, *Crowdsourcing* boosts the number of comments amongst all followers types, reconciling the results of this group with those of the literature (Plandikosa Cvijikj and al., 2013). Lastly, *Defending* boosts the comments amongst the *collision* sports followers, though it lowers them in the collision-free sports followers.

Across Twitter, consistent with previous findings, four *selling* subdimensions decrease engagement, regardless of the sport followed. The other five have no significant effect on consumer engagement. These are *Implicit Selling*, *Product/Family*, *Prize Draws* and *Cross-Promotions*. As we observed at the dimensional level, *collision* sports' followers have a greater tolerance for *selling* contents.

In question two, we observed that *quality* increases engagement. This remains mostly true, but rarely on both metrics and for both groups. Of the twelve subdimensions, only *Hooking* increases engagement on both metrics regardless of the risk of *collision* in the sport followed. Otherwise, the only subdimensions to have the same effect on both metrics are *Bridging*, *Joyful, News* and *Gallery* which increase *relative likes* and *relative comments* among *collision* sports followers. *News* however, decrease *relative comments* among followers of non-collision sports. Twitter is the only SNS where *News* is observed to have a decreasing impact on engagement. Possibly, Twitter users who heavily use the platform as a source of information are more sensitive to the quality of the new*s* delivered to them. Thus, brands that send them ads rather than news via their news feed disengage them (Malhotra, 2012 ; Walker and al., 2021).

Finally, we observed in the third question that, unlike other sports followers on Twitter, *collision* sports' followers welcome *social* content as it increases the number of relative likes among them. A closer look at the subdimensions clarifies this point and informs us that *Bonding* and *Crowdsourcing* only increase engagement among *collision* sports fans, whereas they reduce it among non-collision sports followers.

In short, on Twitter, across all subcategories, only Hooking increases the number of likes and relative comments, regardless of collision risk. The list of subcategories that increase engagement grows when considering only collision sports followers. Bridging, Joyful, Gallery and Bonding are added as sub-dimensions.

Across Instagram, of the nine *selling* subdimensions, only one, *Events/Tickets* , decreases engagement on both metrics, across all followed sports. With respect to question two, we observed that Instagram was the most *selling*-resistant and, at the same time, the SNS that featured the least amount of *selling* content. Out of the more than 1,600 *selling* posts analyzed, it's only on Instagram that a *selling* subdimension, namely *Prize Draws*, increases consumer engagement. The reason *Prize Draws* increase *relative comments* among *collision* sports followers is perhaps that those who enjoy experiencing the excitement of *collision* and violence in sports, also like experiencing the excitement of the chance of winning a prize (Bryant and al. 1983). They are looking for that fun feeling characteristic of audiences on Instagram (Coelho and al. 2016).

In terms of quality, our results in question two run counter to the existing literature that claims that *quality* increases consumer engagement (Ding and al, 2014 ; Doyle and al, 2020 ; Subramani and Rajagopalan, 2003 ; Nepomuceno and al, 2020). Some subdimensions confirm these results while others contradict them. It is true that the publication of *Immersion* and *Gallery* contents decreases engagement among all sports followers. The results from *Gallery* are at odds with those from Facebook and Twitter, where *Gallery* increases engagement every time, with only one exception. We suspect this difference is due to the environment, the context. Due to the large number of photos shared on the platform, consumers experience what Bai and al. (2020) call overload. Overload causes high quality photos, published by organizations, to be perceived by consumers as inauthentic. Photos taken by fans, while of high quality, are not perceived as inauthentic and do not decrease engagement (Doyle and al., 2020). The *News* and *Hooking* subdimensions rather go in the direction of the literature and increase engagement among collision and non-collision sports fans. As well as *Joyful* posts which generally increase engagement as well.

For the *social* dimension, while we were under the impression that it did not significantly impact engagement, three subdimensions have a significant effect on engagement. These subdimensions are *Bonding*, *Behind the Scenes* and *Crowdsourcing*. The results of the *collision* sports followers, pose a dilemma for content managers. Publishing one of three types of content increases one of the measures (*relative likes* or *relative comments*) and decreases the other (*relative likes* or *relative comments*). Impact is therefore both a gain and a loss. Among the followers of non-collision sports, the trends are clearer. *Bonding* and *Crowdsourcing* increase both *relative likes* and *relative comments while Behind the Scenes* decreases both metrics.

5.3 Practical implications

Gone are the days of the famous Saturday Night Hockey Mass or the Sunday Night Football Game enjoyed by the whole family. Youths go about their own business, on streaming TV, their phones or social networks. As a result, sports fandom among young people has been dropping for the past decade. Although most sports organizations have a social media presence, they are not appealing to members of Generation Z - born after 1996. For leagues like the NFL, unless there is a turnaround, the next generation of consumers will not show up in 10-15 years (Maese, 2020). Many leagues are looking to attract new fans and expand the traditional sense of a fan that buys season tickets and watches games on television. Sports organizations are increasingly interested in the digital consumption of content (Maese, 2020). The results of this study have important implications for many people interested in the professional sports industry. Persons interested in sports sales and research will find the moderation effect of *body collision* on the relationship between content and engagement very useful. Among other things, it notes the importance of differentiating between fans of different sports when it comes to posting content on social networks. Dividing them into two groups offers interesting possibilities. The case of *quality* on Facebook, for example, is a resounding success on all fronts for *collision* sports, while predictions were rather mixed for all sports. And that's not to mention the case of *Prize Draws* among *collision* sports fans that increases engagement on Instagram, which is the only successful sales offensive.

For researchers and content managers, this study offers insights into which content publishing strategies are most likely to increase engagement on each social network. It also gives them a good idea of which strategies they should avoid in order not to significantly decrease engagement. By comparing the descriptive statistics and the results of our regressions, it appears that engagement is not only the result of the published content moderated by both the *collision* risk and by the platform. There is a fatigue effect among followers. When organizations post too much of the same content it results in a form of overload and decreases engagement (Bai and Yan., 2020 ; Nepomuceno and al, 2020).

For researchers and brand specialists, this study offers insights into the trust to be maintained between followers and organizations. While Twitter is a network where 55 % of its users go to see news, the publication of *News* brings down *relative comments* among sports fans without collision. Subscribing to organizations' news feeds, they claim their trust has been betrayed, saying they are turned off by the brand, when instead they are sent promotional content (Malhotra, 2012 ; Walker and al., 2021).

All these insights should have a direct effect on how to choose the right contents published on each network, catering to each community of sports followers. In a nutshell, brands should avoid the " *one size fits all* " approach (Wahid and Gunarto, 2021).

5.4 Recommendations for Further Research

The purpose of this study was to examine how the interrelationship between content published by businesses and choice of social media platform can impact customer engagement. Data was collected and then analyzed to answer the four research questions related to this objective. Many meaningful findings emerged from this research.

While significant, they do have some limitations. One limitation is that the findings of our study only explain the moderating effect of three social networks.

Once the analysis of the data began, an article was published on Statistica stating that YouTube is the preferred platform for sports fans who listen to Highlights (which alone represent 72 % of all the quality posted by our sample). Furthermore, the article listed Snapchat, TikTok and Reddit among the top ten platforms, all of which are absent from our analysis (Statistica, 2020). Future research on the subjects could benefit from exploring these networks that are gaining in popularity

This study also faced large amounts of unstructured data. Structuring it without losing sight of the original research objectives was demanding. If time and manpower had not been an issue, the data could have been structured more thoroughly. Given our resources, *Vividvess* was only coded into text, images, carousels, GIFs, or videos. Given more time, as well as access to computer-assisted speech analysis, future researchers could classify videos by multiple facets, structure them even by voice, nuance them by pitch, speech rate, and intensity (Balducci and Marinova, 2018). Because not all videos are similar, some are bound to engage followers more than others. Structural features known to influence user engagement, such as days and times of publication, could also be added as control variables in a future study (Pletikosa Cvijikj and al., 2013)

Finally, the original goal to have as random a sample as possible was not quite reached. Indeed, as the three researchers reside in Canada, when considering which sports to cover in their study, their knowledge was limited and colored by their background. America is overrepresented with nearly half of all data, and other continents underrepresented with only five percent from Europe, about eight percent from Asia, and about five percent from

Australia. If the data from the study was representative of the overall sports market, America would account for 35 %, while Asia would account for 30 %. (GlobeNewswire, Markets et al, 2021). This imbalance shows we are not adequately examining overseas teams and sports organizations, which make up a significant portion of the global market. Future research could benefit from a fair comparison across markets.

5.5 Conclusions

The findings of this study have extended the work of previous researchers in the area of consumer engagement and firm generated content on Twitter, Facebook, and Instagram. The fit between content dimensions and these networks is critical as significant differences were found between each (Zhang and al.,2017). *Selling* decreases engagement on all networks. *Quality* fit is highest on Twitter where it increases both *relative likes* and *relative comments*. It is at its lowest on Instagram where it decreases *relative comments*. The *social* dimension has zero impact on engagement on all networks with the exception of Facebook where it decreases engagement.

A further examination of the subdimensions results confirmed that, since the four dimensions are composite measures, no component is interchangeable, and they are frequently non-correlated with the dimensions to which they belong.

Lastly, our study revealed that context also influences consumers' online engagement. The fit between users and the types of content they enjoy is not only influenced by the network they use, but also the sport that they follow according to the collision risk involved. Indeed, collision sports fans react to firms' content publishing significantly differently than non-collision sports fans. For organizations to stand out in a context of content overload, they must adapt their contents across platforms and across sports. In doing so, they will succeed in rising above the fray.

5.6 Declaration of Conflicting Interests

The author(s) declares no potential conflicts of interest with respect to the research, authorship, and/or publication of this thesis.

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Appendices

Appendix A – Coding Grid

Architectural Dimension

Brand	Here you should insert the brand related to the post.
Country	Here you should insert the country related to the page which you are scraping. To switch countries, you must click the "…" button, then click on the "Switch region" button, and select the country that you are interested in.
Platform	Here you should insert the social network related to the post : Facebook, Twitter, or Instagram.
Post date	Here you should insert the date of the post. You should start from the oldest post. If a page has more than one post per date, then you should add a line, repeat the date but use a different post number.
Post number	The default for this should be "1" You should use number "2" for the second post in a given day. Use number "3" for the third post, so on and so forth.
Post text	Here you should paste the text posted by the artist on Facebook (you will later use this text for TEKST described further below).
Text	You should count the number of words and insert the total here.
Video	If the post has a video or a link to a video, please insert here the total length of the video in seconds. If no video was inserted, please insert the number "0".

Images	If the post contains image(s), please insert here the total number of images inserted. If no image was inserted, please insert the number "0".
Live streaming	If the post has a link for a live streaming (radio or TV), which might or might not be active, insert "1" if it is present but not active and insert the total number of seconds if it is active. If it has no streaming, please insert the number "0".
Audio	If the post has a link for a radio interview or radio audio of any type, please insert here the total number of seconds of the audio. If it has no audio, please insert the number "0".
Carousel	If the post has swipeable photos and/or videos, insert "1". If it has no carousel, please insert the number "0". Applicable to Facebook and Instagram.
Pool	If the post has a vote pool, insert "1". If it has no pool, please insert the number "0".
Paid	If the post has a "paid" label indicated beside the date information, insert "1". If it has no paid label insert the number "0". Applicable to Facebook. As paid posts are personalized, it may be present for an account profile or not, while a different post may be present in the other account profile or not. It is possible to know how many ads (paid posts) and to see each one of the ads are actually running in one location, by selecting the option 'Info and Ads' on the brand page menu.

Shares	Simply register the number of shares of the given post. Not suitable to Instagram.
Like/ love/ wow/ hahaha/ angry/sad	Simply register the number of like/love/WOW/Hahaha/Angry/Sad(s) of the given post. Instagram and Twitter have only "likes".
Comments	Simply register the number of comments of the given post.
Video views	Simply register the number of views of the given post. Please insert here the total number of views of the video. If the video has no views, please insert the number "0". If the number of views is not available, keep the space blank. The views numbers could be not available when the video is a GIF or it is in a carousel.

Selling dimension

Type of Post	Description
Explicit Selling	Insert number "1" if the post explicitly sells products (direct purchase, link, or the like). "0" otherwise.
Implicit Selling	Insert number "1" if the post implicitly sells products, but without explicitly pushing the sale. "0" otherwise.
Product/ family/ merchandise	Insert number "1" if what's being sold (implicitly or explicitly) is a product or products of the same family. This also includes merchandise of the Player/Team/League. "0" otherwise.

Price	Insert number "1" if the post indicates a price (or a special price). “0” otherwise.
Subscriptions	Insert number "1" if what’s being sold (implicitly or explicitly) is a subscription that give access to discounts, test, free items, etc.), “0” otherwise.
Event marketing	Insert number "1" if what’s being sold (implicitly or explicitly) is provided in an event organized by the Player/Team/League. Examples of such events are free samples in a festival ; brand kiosk in a specific address during a pre-defined period where it is possible to live an experiential marketing action ; festivals, reunions, marathons, concerts, or other sponsored gatherings. The goal is to motivate fans to attend an event which will then motivate further purchase at the event. “0” otherwise.
Events/ tickets	Insert number "1" if what’s being sold (implicitly or explicitly) are tickets to a match, game event or the like. This category also includes links or channels for watching games or sports-related events. “0” otherwise.
Prize Draws	Insert number "1" if what’s being sold (implicitly or explicitly) includes prize promotions. It may be money, other products, or any kind of reward (i.e. Enter the code printed on the product packaging into a website to see if you won a prize). “0” otherwise.
Cross-promotion	Insert number "1" if what’s being sold (implicitly or explicitly) is a non-sports-related merchandise, a brand, a company with a COMMERCIAL objective. Insert “0” otherwise

Quality dimension

Production process of Product/ product family/ merchandise	Insert number "1" if the post demonstrates the product quality by presenting images, videos or audios related to the production process of products, product family or merchandising (e.g., images of the product while packing, work in progress, new features, images of the production process universe). “0” otherwise.
Development of Team/ Players/ League	Insert number "1" if the post presents the training and recruitment (ex : NFL combine) process of players, coaches, teams, leagues, etc. “0” otherwise.
Hooking	Insert number "1" if the post brings action to the value of the sport, league, or team’s players (a recognition, an award, a popular vote, …). This may include feats by players/teams that are remembered and recognized years later. “0” otherwise.
Player/ Team/ League Description or Stats	Insert number "1" if the post includes a detailed description of a player, team or league stats (e.g., analytics related data for sport junkies). “0” otherwise.
Immersion	Insert number "1" if the post describes the **story behind** a Player/Team/sport/League, the background of its universe. “0” otherwise.

Bridging	Insert number "1" if the post connects with other events, organizations and domains with a NON-COMMERCIAL objective (e.g. A cruelty-free organization, an institution, a holiday, a trending topic, etc). “0” otherwise.
Bridging People	Insert number "1" if the post connects with personalities and social influencers, either a person, a family, or fictional characters. The objective of this connection is to portray a Player/Team/sport/League quality. “0” otherwise.
Healthy	Insert number "1" if the post presents healthy benefits and features related to the sports universe. “0” otherwise.
Joyful	Insert number "1" if the post presents a situation that is joyful for the consumers (e.g., product consumption ; humorous advertising ; etc.). “0” otherwise.
News about the team/ league/ players	Insert number "1" if the post relates to news and information about players, teams, coaches, league, etc. The goal is to update fans about the latest facts and news (e.g., trading of players, new hires, match scores (half-time scores, press conferences with insider views, etc.). This does not include analyses of the game. “0” otherwise.

Gallery/ Artistic	Insert number "1" if the post demonstrates the quality by presenting concept-art images, videos, or audios (e.g., images of creation of merchandising or sports-related products). This content dimension may also include a picture/video/audio of the performance by an athlete, coach, mascot, or cheerleader (e.g., Michael Jordan flying to dunk a ball). This content must demonstrate quality by presenting the high performance (player in motion) of someone in the team/league universe. Insert "0" otherwise.
Highlights	Insert number "1" if the post presents highlights from recent games from the team or the league (e.g., match winning play). It's an action taking place during the game that is often used as a way to present the quality of the team or league. Insert "0" otherwise.

Social dimension

Bonding	Insert number "1" if the post aims at developing a sense of attachment with existing fans. Insert "0" otherwise.
Evangeli-zation	Insert number "1" if the post aims at alerting existing consumers/fans to attract new consumers/fans. Insert "0" otherwise.
Defending	Insert number "1" if the post aims at involving existing fans in protecting or supporting the team/league/player in the broader community. Insert "0" otherwise.

Social Spotlight	Insert number "1" if the post aims at bringing to the spotlight content created by fans. These posts motivate fan engagement with the community and encourage fan interaction through community-driven content. Examples of these posts are the ones showcasing material created by fans (e.g., photos, signs made by fans or using merchandise products). Insert “0” otherwise.
Small Talk	Any post that starts a conversation without an explicit purpose of creating a sense of attachment with existing fans (examples : posts that have little or nothing to do with the game or creating a bond with the audience).
Intimacy	Insert number "1" if the post generously reveals something about the team/league/player.
Behind-the-scenes (Between the scenes)	Insert number “1” if the post showcases intervals, time-outs, downtime, and other exclusive moments in between matches or games that are not necessarily portraying the teams/players' quality. The purpose of these posts is to connect with fans. Insert “0” otherwise.
Crowd-sourcing	Insert number "1" if the post aims at inviting fans to contribute to the development or promotion of the product (e.g., by moderating forums and chats ; by reporting inappropriate content ; by voting on favorite colors or items ; by voting on posts ; or by asking consumers to engage in the community to give away). Insert “0” otherwise.

CSR/ Charity	**I**nsert number "1" if the post brings social responsibility actions about the team/league/player. It includes investments in sustainable process, socially responsible, reusable inputs, or if it is inviting members to play an active role in favor for social causes. “0” otherwise.

Appendix B – Reliability discussions

Introduction :

At the beginning of the coding process, we were three coders (*Student1*, *Student2* and *Student3*) and the teacher supervising the project Marcelo Vinhal Nepomuceno. In the end, we only kept the coding of two of the coders (*Student1* and *Student2*). The notes from the three-way discussion were still kept since they will have guided our coding decisions.

The process notes are crucial because even though each item on the coding sheet had a corresponding definition, some definitions turned out to be vaguer than others. If there was a follow-up project, whether hand or machine assisted coding, perhaps the definition grid could be improved. Here are the different % of disagreements between coders after the grid training phase before the discussions.

All disagreement
86.40 % reliability
=SI(OU((*Student1* !O3+*Student2* !O3+*Student3* !O3=0);(*Student1* !O3+*Student2* !O3+*Student3*!O3=3));"Agree";"Disagree")

Big disagreements
90.75 % reliability
=SI(OU((*Student1*!O3+*Student2*!O3+*Student3*!O3=0);(*Student1*!O3+*Student2*!O3+*Student3*!O3=3));"Agree";"Disagree")

4.35 % difference between big and small disagreements

However, since we only kept the data from *Student1* and *Student2*, there will only be Agreements (0.0 and 1.1) and Disagreements (1.0 and 0.1). All disagreements were discussed until a consensus was reached.

The selling dimension :

The first correction we had to make during our discussions was to add the dimension of *selling*, *implicit* or *explicit*, to all the elements we had coded as sales (*Subscriptions*, *Events*, *News* consistently increase engagement, across all three social networks except for collision-free sports fans on Twitter. Twitter users who overwhelmingly use the platform as a news source have a definition of both what is and is not *News*. The brands that send them advertisements via their news feeds break their trust and turn them off the brand (Malhotra, 2012 ; Walker et al., 2021). The decline in engagement on Twitter caused by *News* is possibly due to the divide between news sent by brands and actual *News*, *Cross-Selling*, etc.).

Explicit selling :

The initial reliability score was 87.62 %. There was a large difference in the number of items identified : *Student1* identified 193 items, *Student2,* 547 items and *Student3,* 61 items. *Student1* had identified several communications where the imperative form was being used, which led him to believe that it was an *explicit* sale.

However, these displays did not always seek to sell anything, hence our disagreement. *Student2*, on the other hand, selected posts that had an active link whether the *selling* message was *implicit*, *explicit* or nonexistent. During our discussions, we agreed that posts needed to have an **<u>explicit</u> <u>call to action</u>** and a **<u>direct link</u>** to be in that category.

Some of those were written in an informative manner (see UFC post below)…not necessarily using the imperative verb tense. Others had a stronger call to action (see Gloucester Rugby below).

<u>UFC</u>

<u>Gloucester Rugby</u>

A few cases, like sarencensofficial, were a bit less explicit because the direct link could only be found in the bio, not quite one click away.

<u>Sarencensofficial</u>

Implicit selling :

The initial reliability score was 70.69 %. There was a large difference in the number of items identified. *Student1* identified 529 items, *Student2* identified 1,280 items and *Student3* identified 23 items. In the sports domain, promotion of upcoming games represents a large part of the publications.

One of the major differences between the coders was that *Student2* considered games and paid sporting events as products sold by organizations, while *Student1* and *Student3* did not.

However, *Student2* was sometimes too flexible with the implicit part of the definition. She viewed all announcements about the upcoming season, such as player selections, to give fans an appetite for the next season.

So, they decided to refocus *Implicit Selling* on messages that **<u>implicitly sell a specific game, product or subscription, not the team in general</u>**.

AusOpen (below) focuses on the players but still manages to implicitly sell tickets for the upcoming season.

Sometimes the implied sales messages are still images "hidden" at the very end of videos, such as the example of a UFC screenshot taken after just over 7 minutes of viewing a fight featuring Joseph Benavidez. These kinds of hidden sales were often missed on first viewing of Student 1 and 3, which accounts for the differences between the number of occurrences coded between each.

Product/product family/ merchandise :

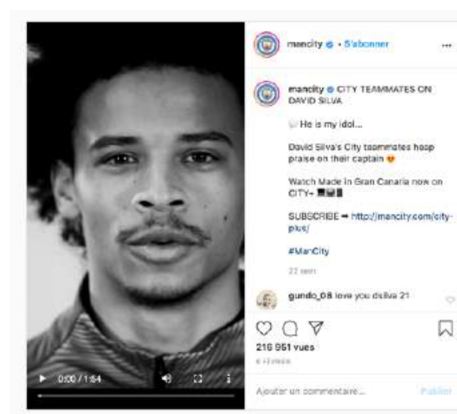
For this category, the initial reliability score is 96.2 %, which is quite good. However, if the score is so high it is because the number of instances is low, not because our understanding of the concept is the same. In this way *Student1* identified 142 items, *Student2,* 80 items and *Student3,* 54 items.

Initially, the way of coding between *Student1* and *Student2* was very different. *Student1* coded all *tickets*, *subscriptions* and matches as merchandise, while *Student2* considered them as *Events / Tickets*. We standardized our coding so that all products under *Product/product family/* **merchandise are products that are not Tickets/Events or Subscriptions**.

The publication of the Mumbai Indians is the typical example (left). The selling of subscriptions to sports broadcasting platforms (ex : Manchester city plus - city-plus) that didn't belong under *Cross-Promotion* were redirected here.

Mumbai Indians

Manchester City



Price :

The initial reliability score of 99.82 % was close to 100 %. The number of items corresponding to this subcategory is however very small : 2 items for *Student1*, 7 items for *Student2* and 1 item for *Student3*. The only disagreements occurred where prices were not mentioned, but rather a reduction percentage (Gloucester Rugby). According to the Webster dictionary, **<u>the term price refers to an amount of money</u>**. Thus, if the publication does not mention any amount of money or a discount in money amount, the publication does not qualify as a price. The Exeter Chiefs Officials publication is an unambiguous example of *Price*.

<u>Exeter Chiefs</u>

<u>Gloucester Rugby</u>

Subscriptions :

The initial reliability score of *subscriptions* is 98.82 %. The number of publications associated with it is quite low : 13 items for *Student1*, 46 items for *Student2* and 10 items for *Student3*. There was some confusion about what was to be included in *subscriptions*. The definition provided in the grid is "*what is sold is a subscription that provides access to discounts, testing, free items*". Many streaming *subscriptions* sell content, access to watch games online and discounts on special events.

In some ways however, what they are selling is more akin to *tickets and events* - "*tickets to a game, gaming event or whatever*." This category also includes links or channels to watch games or sporting events." Streaming subscriptions fall somewhere in between : a subscription that gives inclusive access to watch all games online. Should they then be coded as *subscriptions*, *events/tickets* or both ? We've ruled on both in the example below.

<u>Volleyball Canada</u>

Event marketing :

The initial reliability score of *Event marketing* was 98.84 %. The number of publications associated with it is quite low : 28 items for *Student1*, 38 items for *Student2* and 6 items for *Student3*. There is some confusion between marketing *Events* and *Charity*. Some of the events organized by sports organizations for the community had been identified as *Charity*. We sorted through them by asking whether they were targeting the organization's already acquired fan base and whether these events remained within their universe.

For example, professional field hockey players returning to their hometowns and skating with local junior field hockey teams is *Events Marketing*, not *Charity*. These events reach fans, create content for social media and stay within the same sporting universe. Ultimately, this leads to sales of tickets and seasons tickets.

Although it may be considered social engagement, it is a promotional activity that cultivates a current or future customer market. Some Human Resources recruiting events, open calls for players or cheerleaders were also mistakenly coded as marketing events.

Correct, recruiting players is:

1- **hosted by the team,**

2- **held outside of the regular season**,

However, the purpose of such an event is not:

1 **to motivate fans to attend** and

2- **to encourage them to buy more**. Such events are targeted at semi-professional players who hope to make a career out of playing for the team.

BC Lions

This event, promoted by Joe Gibbs Racing is a good example of what *event marketing* is:

Joe Gibbs Racing

Events/tickets :

The initial reliability score of *Events/Tickets* is 71.83 %. There is a great disparity between the number of publications associated with it according to the coders : 286 items for *Student1*, 1,365 items for *Student2* and 34 items for *Student3*. The number of publications differed greatly between coders as almost all the **match, tournament, and race announcements** that *Student 2* categorized as *events/tickets* were categorized under *news* by *Student 1*. Some go into both categories as below:

Kolkata Knight Riders

Volleyball Canada

Prize Draws :

The initial reliability score of *Prize Draws* is 98.36 %. There is a large disparity between the number of items coded by *Student3* and the other coders : 58 items for *Student1*, 76 items for *Student2* and 1 item for *Student3*.

The concept of *Prize Draws* was very clear. Once *Student3* was removed, the disagreements were due to items seen by one coder and missed by the other. Two pairs of eyes are better than one. Often, *Prize Draws* go hand in hand with *Cross-Promotions*.

<u>Detroit Red Wings</u>

<u>Detroit Pistons</u>

Cross-promotion :

The initial reliability score of *Cross-promotion* is 86.1 %. Once again, coder 3 identified a significantly lower number of publications than the other two coders: 367 items for *Student1*, 558 items for *Student2* and 5 items for *Student*3. *Student2* identified more elements in the *cross-promotion* because she considered all TV/streaming/YouTube channels and radio stations as brands with a commercial purpose. However, after discussion, they **<u>were removed since they are related to sports</u>**.

Cross-promotion, like event sponsorship, takes many forms : while always categorized in the same way, we sometimes saw brands collaborating with teams on a recurring basis by naming players of the week, running special promotions on the team's social media, sponsoring special events, games, or promotional booths, while other brands simply inserted their logo at the bottom of the team's online posts. Below, DMC (Detroit Medical Center) only added their logo at the bottom. Jeep chose instead to mount a tailor-made promotion in collaboration with the NBA to reach fans for greater visibility. eBay has a very different approach. They are creating exclusive content with Bruce Brown from Detroit Pistons, an insider's look into his closet.

<u>Detroit Red Wings</u>

Detroit Pistons

eBay has a very different approach. They are creating exclusive content with Bruce Brown from Detroit Pistons, an insider's look into his closet.

Detroit Pistons

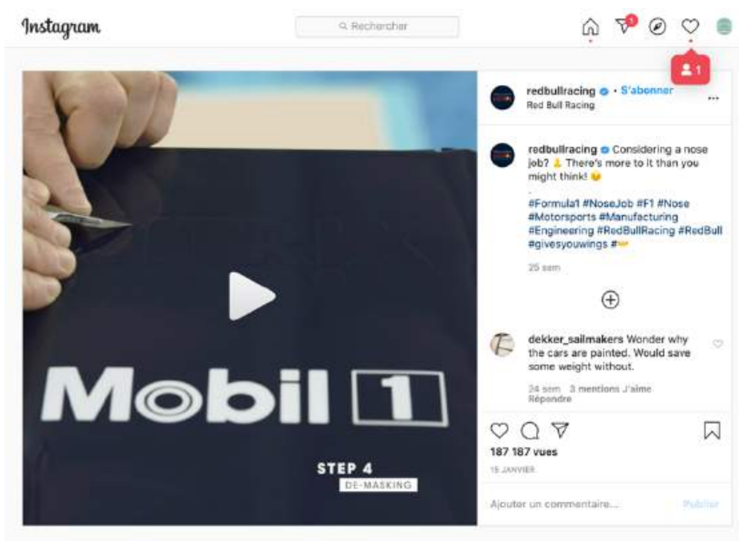
The quality dimension :

The *quality* dimension seems to be much more subjective since the variations are more marked from one coder to another.

Production process of product/product family/ merchandise :

The initial reliability score of *Production process* is 99.76 %. The number of publications associated with it is quite low : 4 items for *Student1*, 3 items for *Student2* and 6 items for *Student3*. When discussing this section, we found very few posts (only 5) that really belong in this section, all other disagreements belong in the *development* section.

<u>Redbull Racing</u>



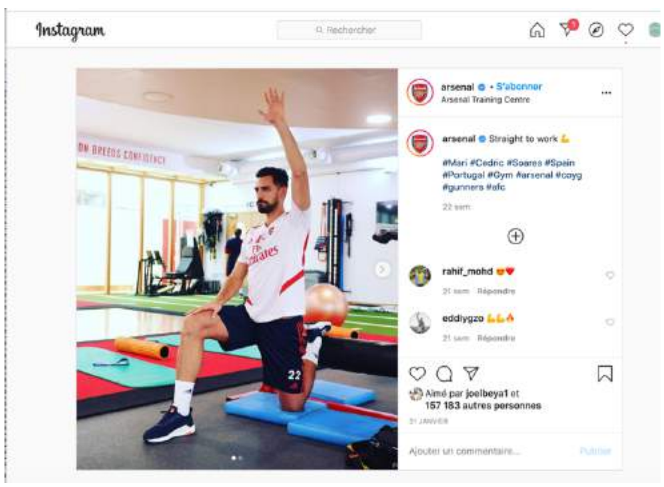
__Development of Team/Players/League :__

The initial *development* reliability score is 95.42 %. The number of publications identified by the coders is quite similar : 154 items for *Student1*, 196 items for *Student2* and 178 items for *Student3*.

We decided to include all **training** info, comments coaches or players made about how practices were going or the type or training they were doing and also included pics in this category.

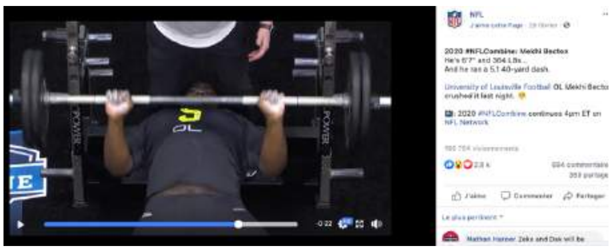
Below is the type of post that fits with the given definition:

Arsenal



Some posts were in a gray area like the drills done during recruitment activities such as the NFL Combine ; they could not be categorized as *news* because no recruitment (hires) had been announced, yet they weren't *highlights,* because they weren't *winning plays during games* either and sometimes they could go under *Gallery* if they depicted *high performance*. We decided they belonged in development : coaches developing a new team.

<u>NFL</u>



Another gray area is when players or a team warm up right before a game. It isn't training as part of a practice but if they are actively practicing and warming up, we did put it under *development*. If they are talking casually, we put it under *Behind-the-scenes* ; it's really a matter of involvement and intensity. In this post, we see two players actively warming-up before a game :

<u>USA Volleyball</u>

Hooking :

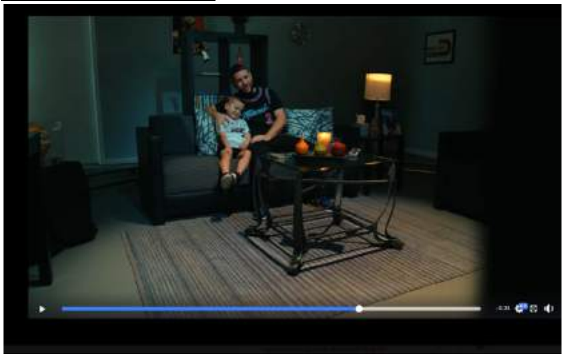
The initial reliability score for *Hooking* is 79.42 %. The difference between the number of publications identified by the coders is quite large : 498 items for *Student1*, 846 items for *Student2* and 303 items for *Student3*. Through the discussions, the disagreeing coder was Student 1 who coded under *Hooking* "*all posts that bring action to the value of the sport, league or team's players*" whereas for *Student2,* the second part of the definition was also essential : "*a recognition, an award, a popular vote*".

Student 1 coded many posts like this one of LeBron James dunking as *Hooking* because "*it brings value to the sport"*. However, it is also in his *Highlights* and *Gallery* category. There is a lot of overlap. For examples like these, we only kept the ones that weren't from recent games – that didn't qualify under *Highlights* – we could say in a way that if they are **remembered years later**, and worth posting after all that time it's because they **resisted the test of time** (that would be a form of recognition- *Hooking*).

Los Angeles Lakers

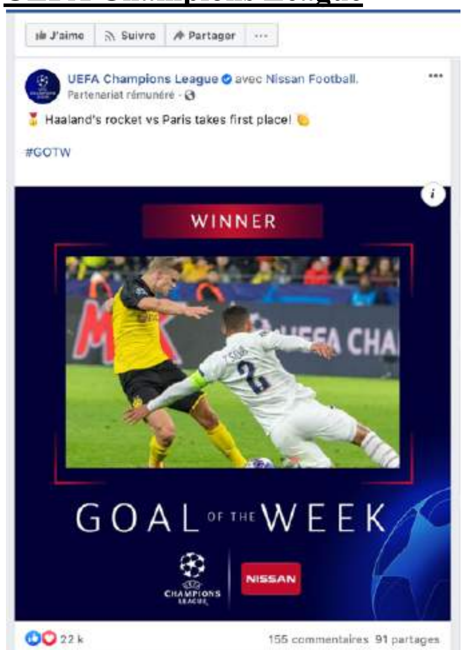
Some awards were unambiguous, like winning Rolland-Garros or this one in honor of Dwyane Wade's retirement :

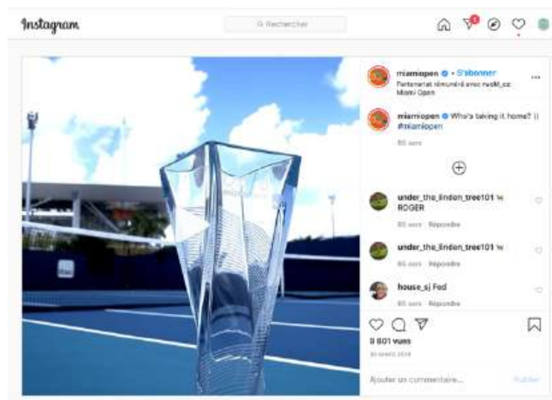
Rolland Garros



Others stretching over a brief period of time (*Goals of the Week* often sponsored by brands) were not always identified by both coders.

UEFA Champions League **Miami Open**



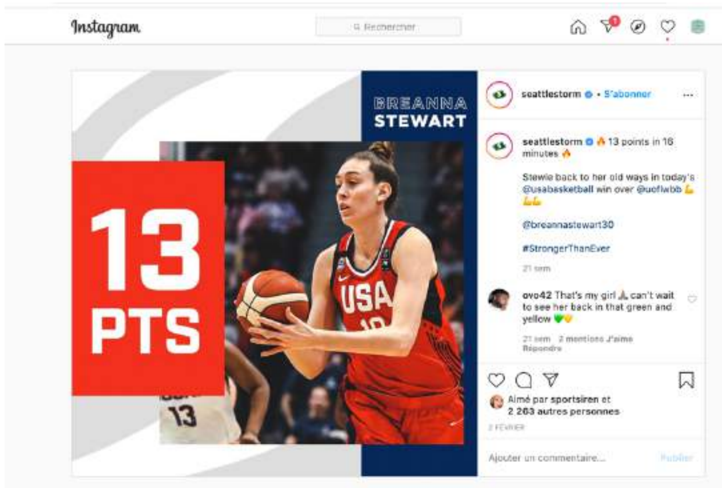


Looking at the numbers however, S*tudent2* coded way more items under that category. Organizations often display their most prestigious trophies in different landscapes (see PGA tournaments above). *Student1* classified those pictures under *Gallery*, *Student2* under *Hooking*. We decided they should go under *Hooking* : "if the post *brings action to the value of the sport, league or a team's players (**a recognition, an award, a popular vote…**)*".

Player/Team/League Description or Stats :

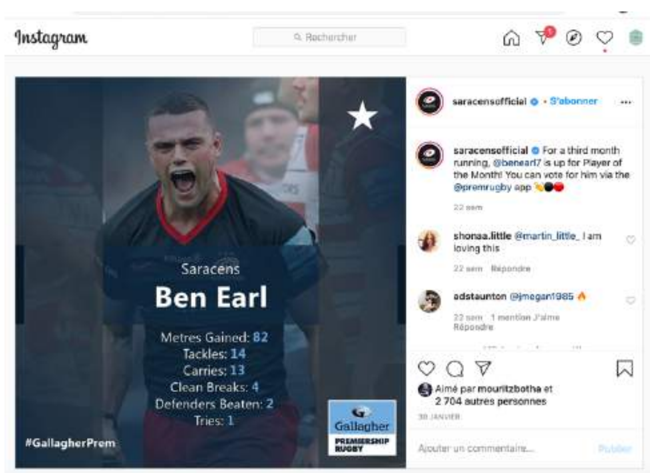
The initial reliability score for *Stats* is 93.36 %. Coder 3 identified a significantly lower number of publications than the other two coders : 199 items for *Student1*, 264 items for *Student2* and 34 items for *Student3*. We established that to be coded as *Stats*, posts had to offer more than a game score.Some posts didn't offer **a lot of numbers** like this one below:

Seattle Storm



Others were a lot easier to categorize and offered a lot of *Stats.*

Saracens Official

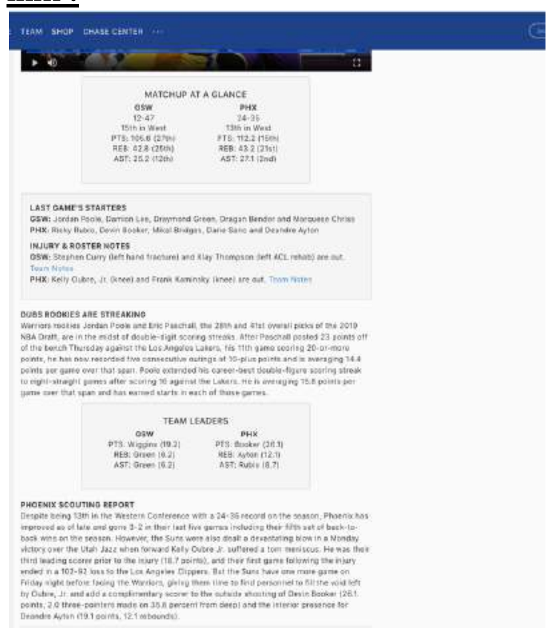


Student2 identified more items because she did not limit herself to the initial messages, but also included the data in the direct links.

In many cases, we could not guess that there were *Statistics* in the links unless we opened them. See the example below of the Golden State Warriors.

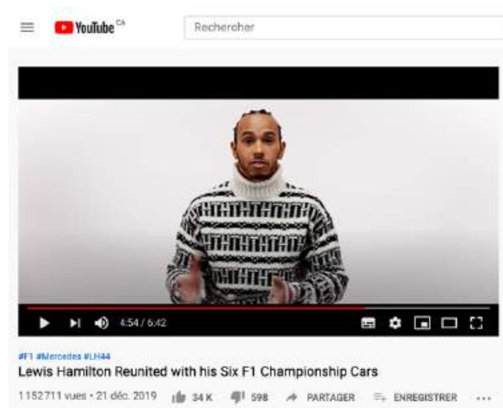
<u>Golden State Warriors -the initial post :</u>

<u>Golden State Warriors-the direct link :</u>



Immersion: The initial reliability score for *Immersion* is 96.42 %. The number of publications identified by the coders doubles from one coder to another : 60 items for *Student1*,
131 items for *Student2* and 33 items for *Student3*. Often, the posts had direct links. In those links, there were sometimes bios with *immersion* features. Immersion is not often in the initial post because of the complexity (length) of that type of content. *Student3* and *Student1* only considered that data in the initial post. *Student2* also considered the data that followed in the direct link : storylines, where the players come from, where they trained, were raised (neighborhood), often players from other teams who have remained friends through the years will talk about first apartments, university anecdotes, etc. * Prof. Nepomuceno ruled that both should be kept. All posts with direct links containing extra data were re-evaluated to compare all differences between the coding files and re-discussed.
This post when analyzed superficially seems to only be a nice photograph of Lewis Hamilton. However, by opening the link and listening to the video of more than 6 minutes, he talks about ethnic diversity, his childhood dreams, the work accomplished to get there, his involvement with the community to make it a better world, and so on and so forth.

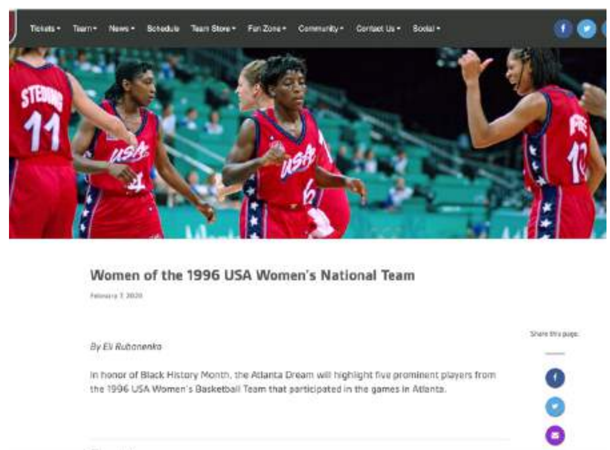
Mercedes F1



Bridging : Inter-group ties*[1] *:

The initial *Bridging* reliability score is 94.96 %. The difference between the number of publications identified by the coders is significant : 60 items for *Student1*, 215 items for *Student2*, and 73 items for *Student3*. Just like *immersion*, posts often had direct links that opened *Bridging* between athletes and black history month, holidays, special days, etc. Again, *Student3* and *Student1* only considered the data in the initial posts. Take this example from the Atlanta Dreams, in the post there was only an old picture (*Gallery*) that could probably be coded under *Hooking, but* it's iconic enough to repost it 24 years later and the caption says : "*She's a star*".

<u>Atlanta Dream</u>



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[1] Sajuria, J., vanHeerde-Hudson, J., Hudson, D., Dasandi, N., & Theocharis, Y. (2015). Tweeting Alone ? An Analysis of Bridging and Bonding Social Capital in Online Networks. *American Politics Research*, *43*(4), 708-738. https://doi.org/10.1177/1532673X14557942

Bridging People :

The initial reliability score for *Bridging People* is 95.8 %. *Student*=1 identified a significantly lower number of publications than the other two coders : 31 items for *Student1*, 133 items for *Student*2 and 93 items for *Student3*. One of the differences between the students is that *Student1* considered all uses of athlete's names outside of official games *Bridging*. *Student1* felt their names were being *bridged* between their professional life and some other context in a promotional matter.

There was also confusion about whether we should consider retired athletes as *Bridging* or not ; this led to many disagreements (see Olympic example below).

<u>Olympics</u>

After looking carefully at the definition provided and a little bit further in the relevant literature : *"Bridging social capital refers to social networks that bring together people of different sorts"*[2] we decided *Bridging* **would be limited to someone outside the organization, the team, or the league.**

Cleveland Cavaliers

We decided to consider retired and deceased athletes as still being a part of the organization. In a way, the teams make that statement when they honor players and retire their jersey to honor them, sort of a way to keep them in the family forever (see Canucks). As for the passing of Kobe Bryant, we did not consider it *Bridging* when basketball teams honored him, because we consider them to be part of the same social networks.

However, when other sport teams did, we did consider it as *Bridging* (see Patriots).

The ATP (Association of Tennis Professionals) is the typical example of *Bridging People* between sports : Luis Suarez, a soccer player, at a tennis tournament.

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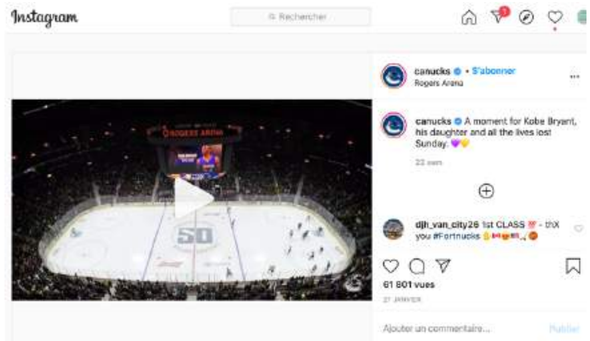
[2] Norris, P. (2002). Editorial : The Bridging and Bonding Role of Online Communities. *Press/Politics*, *7*(3), 3-13. https://doi.org/10.1177/1081180X02007003001

Here are the given examples :

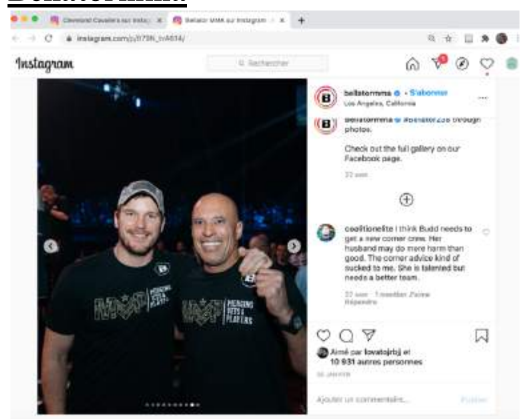
Canucks



Patriots

ATP Tour

Bellatormma



Above, the example of Chris Pratt, a famous American actor, seen in a Gallery of photos at the Bellator MMA is one of the very few examples we've seen of Bridging People between completely different worlds (cinema/sports).

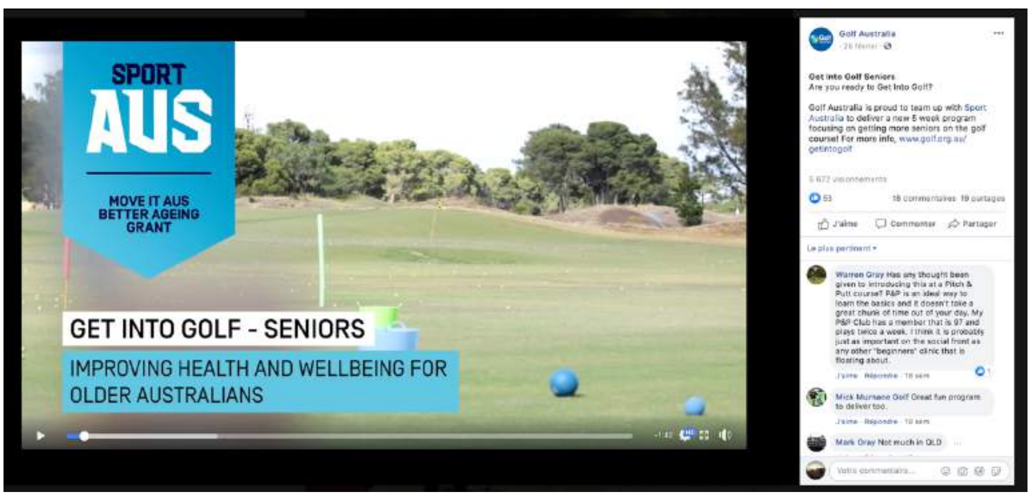
Healthy :

The initial reliability score for *Healthy* is 99.56 %. The number of publications associated with it is quite low : no items for *Student1*, 8 items for *Student 2* and 14 items for *Student3*.

Student3 did not identify these properly as "*post **<u>that present healthy benefits</u>** related to the sports universe"* but rather as charity actions related to health. An example of this is athletes or organizations involved in breast cancer awareness.

We found very few examples of this category, only 7. It might prove difficult to draw conclusions on the basis of only 7 posts out of a sample of 5,000 posts.

<u>Golf Australia</u>

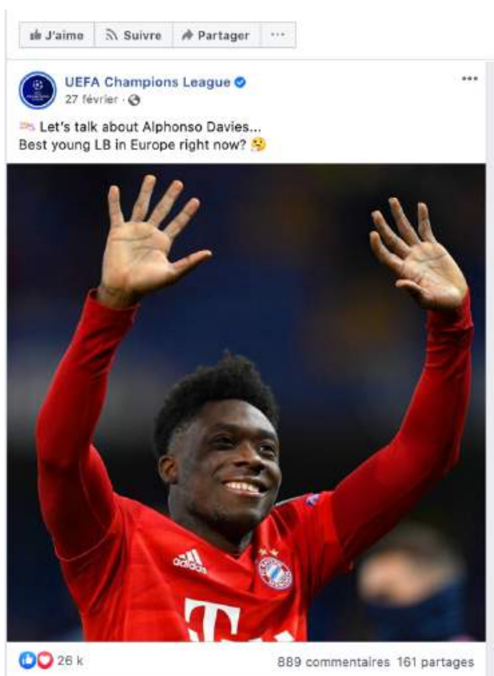


Joyful :

The initial reliability score for *Joyful* is 50.73 %. The number of instances is high and so are the differences between the coders : 622 items for *Student1*, 1,504 items for *Student2* and 2,247 items for *Student3*.

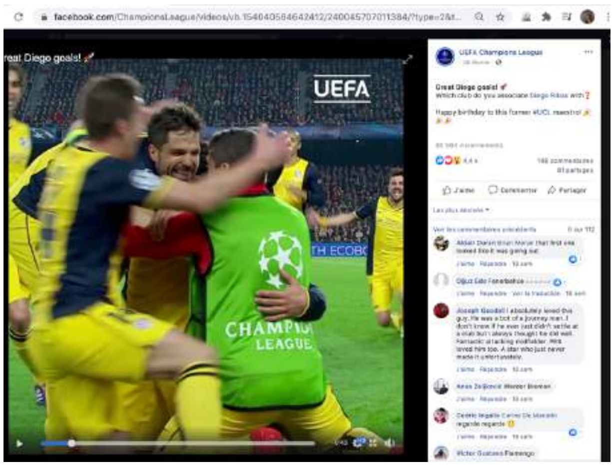
For *Student1* and *Student2*, Joyful is something that you can clearly see in pictures or videos such as smiling or laughter. For Student 3, the *Joyful* quality is more situational. He coded joyfulness when a great play was shown, because he felt it must have been a *Joyful* moment for the player and the fans. When a winning moment was depicted, even if nobody was shown smiling or celebrating, he coded it as a *Joyful* moment. He coded in the second degree with empathy, by putting himself in the player's shoes or in the fan's position. We agreed to code as *Joyful* what we saw objectively in the picture, palpable joy, measured in smiles, laughter, and joy. This post by UEFA Champions League is undeniably *Joyful*.

<u>Champions League</u>



Many of the highlights were also coded as *Joyful*. Often when players made a *match winning play*, it was followed by a very joyful celebration of some sort.

<u>Champions League</u>



There seems to be differences in the way of expressing joy from one sport to another, different social codes, conventions. During our conversations, we found less joyfulness in the highlights among rugby teams. When players score a goal, rather than flashing a big smile like hockey and soccer players do, they pat each other on the back, kiss on the cheek or only half-smile with restraint.

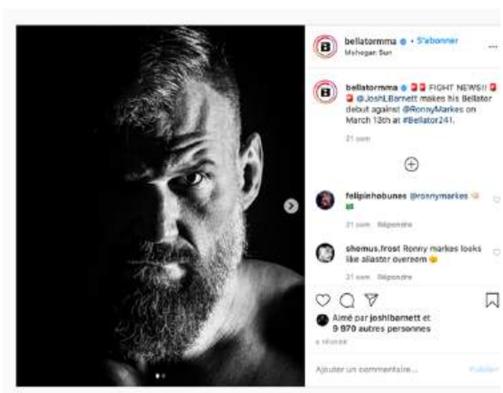
<u>Bath Rugby</u>

News about the team/league/players :

The initial reliability score for *News* is 49.25 %. *Student3* identified a significantly higher number of publications than the other two coders : 1,913 items for *Student1*, 1,016 items for *Student2* and 2,774 items for *Student3*. Some *News* were clearly identified in the coding sheet : trading of players, new hires, match scores. However, there were a few blind spots such as post-match press conferences with coaches and players that forced us to expand our definition of *News*. These conferences mostly consist of coaches and players discussing their feelings and opinions about how matches went. Should they be considered such as locker room talk in between matches, where organizations discuss their feelings, regrets, and things they would have done differently - belonging in *Behind-the-scenes* ? Or as new information/facts belonging in *News* ?

After discussing the issue, we realigned *News* around the **type of *News* that would make it into the sports night bulletin** (**new facts and info**), content larger than event, ticket promotion or match recaps. Often, organizations present matches, fights, games and events as *News* (MMA) Instead of hard selling to consumers, they use a literary style similar to the one you'd find in a press release. This added to the coding confusion, but those belong under Implicit sales, or Events/Tickets.

Bellator MMA titles : *FIGHT NEWS*:



Conversations about impressions, strategies, joys and regrets about how matches went , such as locker room talk were coded in *Behind-the-scenes*.

Here is an example of a publication classified under News :

<u>Winnipeg Blue Bombers</u>

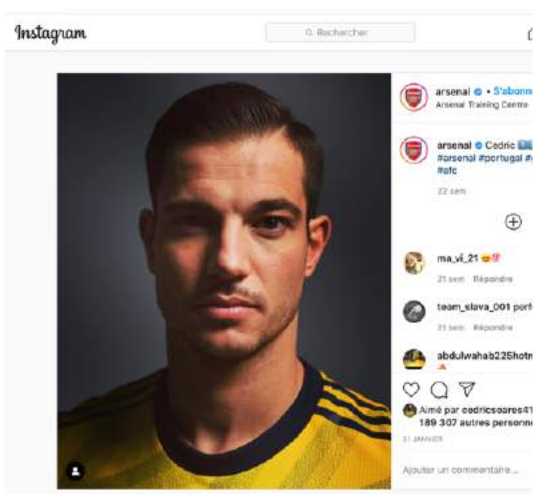
Gallery/Artistic :

The initial reliability score for *Gallery/Artistic* is 34.57 %. *Student1* identified a significantly higher number of publications than the other two coders : 3,257 items for *Student1*, 689 items for *Student2* and 2,406 items for *Student3*.

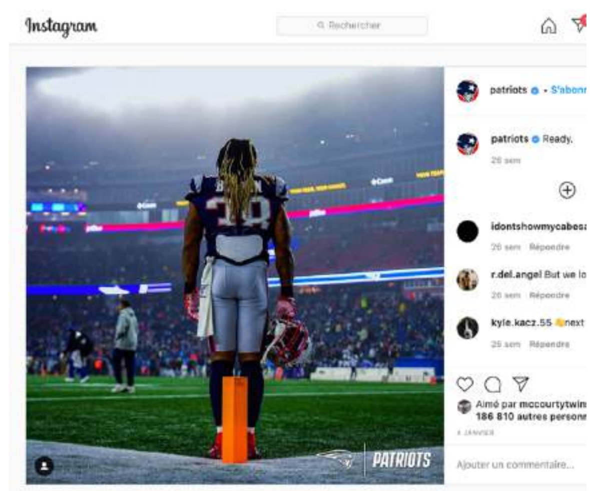
The *Gallery* category raised a lot of questions. For *Student2*, **artistic** pictures are pictures you could hang on your wall, pictures you would see at the World Press Photo Exhibit. For Student 3, all pictures taken with a professional camera are artistic, which is the case for most photos posted on Instagram, Facebook and Twitter, except for those taken by fans.

Many pictures like the portrait below and the very artistic picture taken of a Patriot football player on the field but not in the middle of a high-performance stroked controversy and disagreement.

Arsenal

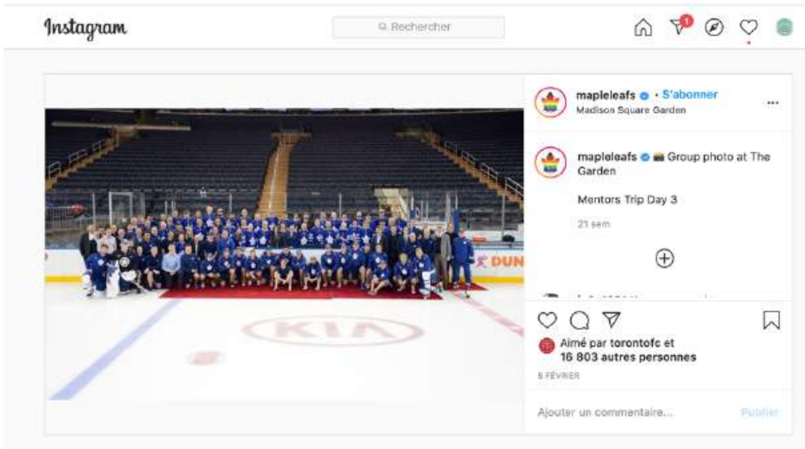


Patriots



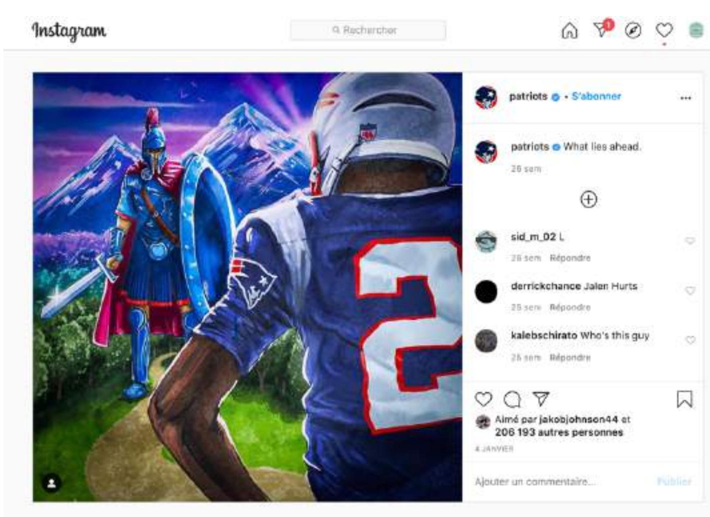
The same goes for group photos (just like class photos, there is nothing remotely artsy about them).

Maple Leafs



And lastly, there was the case of graphic art, usually not depicting a high performance but used more as a way to depict a myth of honoring the team or a player. It did not quite fit into any category either:

Patriots



The pictures above did not correspond to the given definition : "*a picture of the performance by an athlete…this content must demonstrate quality by presenting the high performance*". But where did they belong in the definition grid ?

For *Student1*, all videos where a player scores a goal, a point, a hole in one, a memorable pass is art in itself. For him, there is artistry in a great performance. This explains the large number of items he identified as *Gallery/Artistic.*

We decided that artistic photos **needed to show movement, a high performance or set itself apart from other pictures from an artistic point of view** : a blurry background, a filter, the choice of lighting, choice of aperture, etc.

When considering videos in the *Gallery* performance, we reminded ourselves not to forget that artistry mattered, the final product, but what prevailed was the quality of the performance.

Highlights :

The initial reliability score for *Highlights* is 75.26 %. Student3 identified a significantly lower number of publications than the other two coders : 138 items for Student1, 900 items for Student 2 and 1,147 items for Student3.

There remains some confusion between the *Highlights* and the *Gallery* because many overlap. The only clear difference is **<u>that highlights have to be recent and depict a winning moment,</u>** instead of a high performance.

This post from the **Detroit Red Wings** is a high performance by an athlete that's also a winning play.

The social dimension:

Bonding : (Intra-group ties)[3]

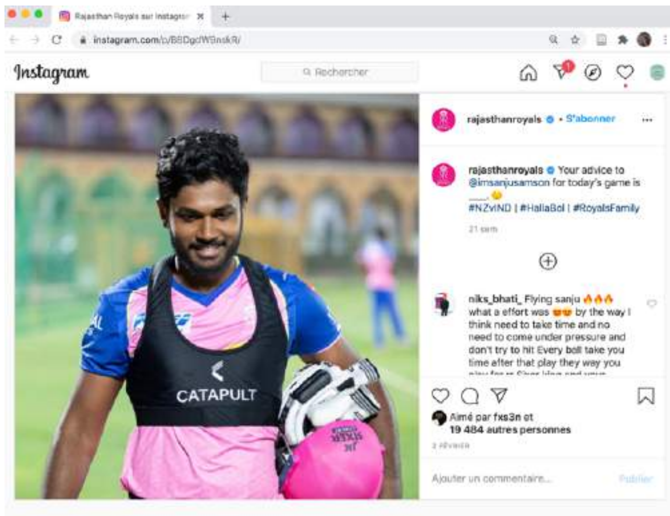
The initial reliability score for *Bonding* is 70.63 %. *Student1* identified a significantly higher number of publications than the other two coders : 1,246 items for *Student1*, 416 items for *Student2* and 221 items for *Student3*.

Student 1 is a sports fan. He felt organizations were trying to bond with him whenever they were asking him to vote, communicating about wins, hires, and showing recent feats. He therefore put all *Crowdsourcing* under *bonding*. *Student2*, on the other hand, felt more *bonding* when there was *intimacy* or *Behind-the-scenes* content involved. We decided to re-evaluate *bonding* and make it **more about tone** – about **organizations talking directly to fans, the consumers** : *Who you got* ? *Tell us where you were when …. Happened* ? An athlete talking directly at YOU looking into the camera, as they would with a friend, often using a language that a neophyte would not understand. When re-evaluating if it was *bonding* or not, we would ask ourselves the following question : "Is the organization strengthening or trying to strengthen the existing relationship with the fan ?" If so, it consists of bonding. Here are three examples of *Crowdsourcing,* the first two with *bonding*. The last, without.

[3] Sajuria, J., vanHeerde-Hudson, J., Hudson, D., Dasandi, N., & Theocharis, Y. (2015). Tweeting Alone ? An Analysis of Bridging and Bonding Social Capital in Online Networks. *American Politics Research*, *43*(4), 708-738. https://doi.org/10.1177/1532673X14557942

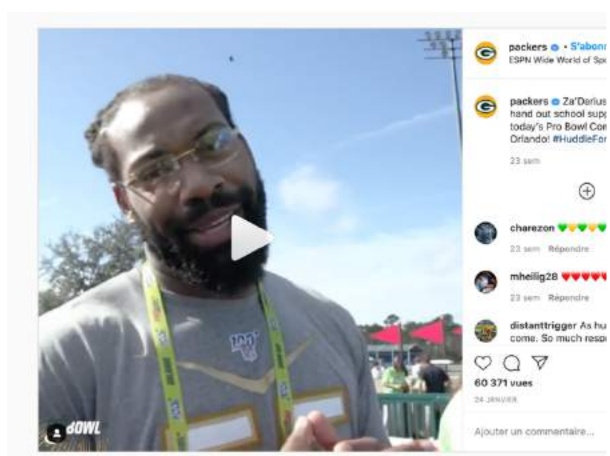
The Rajasthan Royals want "*your*" advice because they cherish *your* point of view and *your* relationship.

Your advice to @imsanjusamson for today's game is ____. 🤔



This Kolkota Knight Riders example is interesting because is says something about the story behind the player, connects with him on a human basis : he too had heroes growing up, before asking fans to share theirs. Others were more subtle, depended more on perception, like the two examples below.

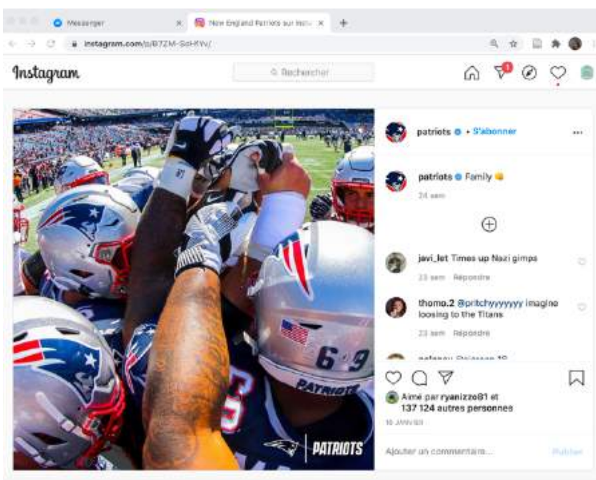
Champions League **Packers**



These explain the low % of reliability between coders. Green Bay Packers' post featuring Darius Smith who has been handing out school supplies illustrates these intricacies.

There were errors in the initial coding, posts coded as *Bonding* when organizations were talking to athletes between quotation marks, instead of talking to consumers, or depicting players bonding together like the post below by the New England Patriots – *They are a Family* but are the consumers included ? This is unclear either way.

<u>New England Patriots</u>

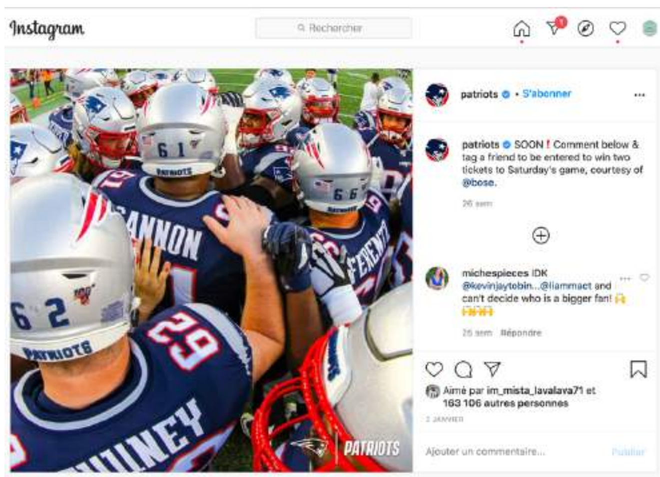


Evangelization :

The initial reliability score for *Evangelization* is 99.76 %. However, the number of publications associated with it is very low : 3 articles for *Student1*, 6 articles for *Student2* and 3 articles for *Student3*.

After further discussions, only three posts truly corresponded to the e*vangelization* definition : "*if the post aims at alerting existing consumers/fans to attract new consumers/fans"*.

<u>Patriots</u>



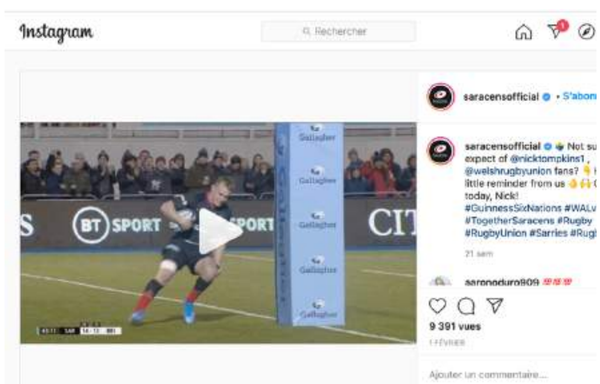
Defending :

The initial reliability score for *Defending* is 97.6 %. However, the difference between the number of publications identified from one coder to another is large : 9 items for *Student1*, 108 items for *Student2* and 5 items for *Student3*. *Student2*'s defending definition is broader than *Student1*'s. *Student1* focused more on the first part of the definition *protecting,* which we saw very little of, very short posts with mentions like *go team* !

We decided to re-evaluate the coding to include the *supporting*, *encouraging* part of the definition, thereforethereby including press conferences in which coaches were excusing the players and defending them.

Saracens Official :

Go well today, Nick !



Rajasthan Royals :

You've come a long way.
It's time to go all the way. 💪
Good luck to 🇮🇳 for
the #U19CWC semi-final 🆚 Pakistan.

Social Spotlight :

The initial reliability score for *Social Spotlight* is 99.06 %. However, the number of publications associated with it is very low : 17 items for *Student1*, 20 items for *Student2* and 15 items for *Student3*.

Student2 had a few more items because since the definition said : ***bringing to the spotlight content created by fans*** but did not specify if the content had to be virtual, she included signs that fans made brought to the spotlight to *motivate fan engagement.*

A good example of that was a little boy standing next to his little brother at a hockey game who had made a sign that read : *Will exchange my little brother for a hockey puck*.

The organization took and shared a photo of the sign to have an impact on the community's engagement.

Detroit Red Wings **Philadelphia Flyers**

Small Talk :

The initial reliability score for *Small Talk* is 93.96 %. *Student1* identified a significantly higher number of publications than the other two coders : 198 items for *Student1*, 42 items for *Student2* and 68 items for *Student3*.

For *Student1*, all birthdays and holidays were coded as *small talk*, so his numbers were higher than *Student2*. *Student2* coded birthdays under *intimacy* and holidays as *Bridging*. Under *small talk*, we coded many posts that have to do with days of the week :

Monday-fun day, Friday – pay day, etc. ***posts that have little or nothing to do with the game***.

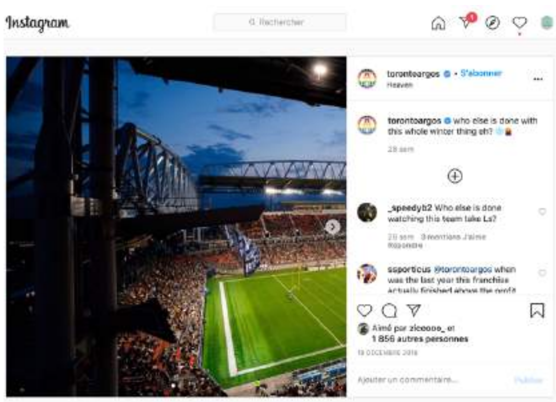
Rajasthan Royals

When Friday is Payday too ! 🏏 📸

Posts that have nothing to do with sports, such as conversations about weather and pizza toppings :

<u>Toronto Argos</u>

Who else is done with this whole winter thing eh ? ❄️🤷♀



<u>Boston Celtics</u>

Pineapple on Pizza ?

Intimacy :

The initial reliability score for *Intimacy* is 91.92 %. *Student2* identified significantly more publications than the other two coders : 92 items for *Student1*, 362 items for *Student2*, and 68 items for *Student3*. *Student2* coded all birthdays as *intimacy*. *Intimacy* is very subjective. Age is intimate to some but not to others. We found it's more intimate for *Student2*, an older woman, than for *Student3* and *Student1,* both younger men. We then decided we would code it as such.

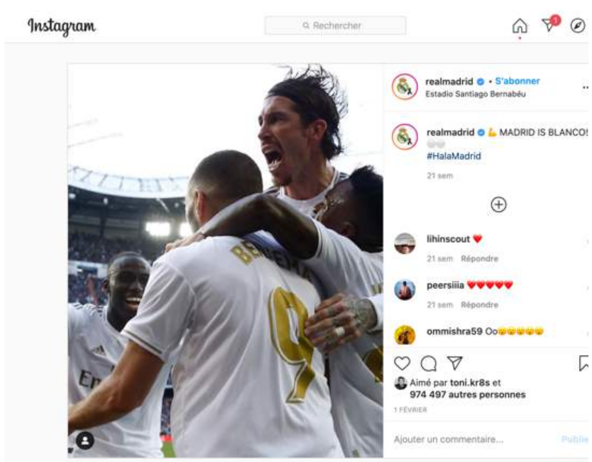
Also, through our discussions, we noticed that physical contact such as touching and hugging is very cultural in its essence and perceived in our coding as more intimate between male team players than between women team players. How much do players need to touch to make it intimate ?

Leinster Rugby : Not touching enough to be intimate :

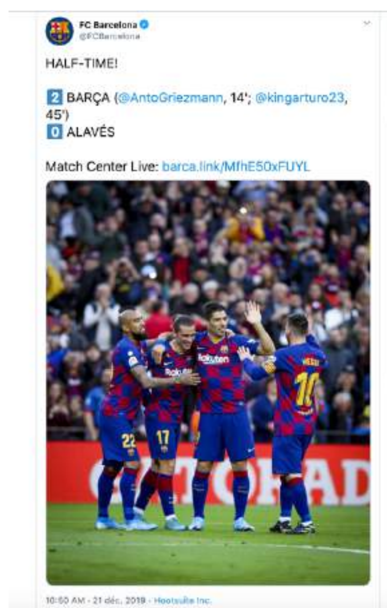
Leinster Rugby women : The touch in this case seems more collegial than intimate.

Here, in all 4 cases, the touch is genuine. We did not want to divide between celebration touch, collegial, friendship, etc.

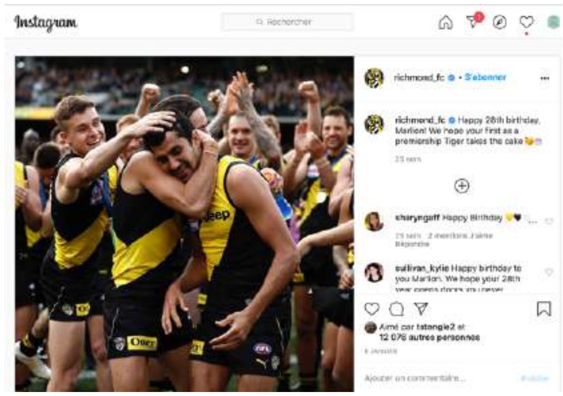
Real Madrid



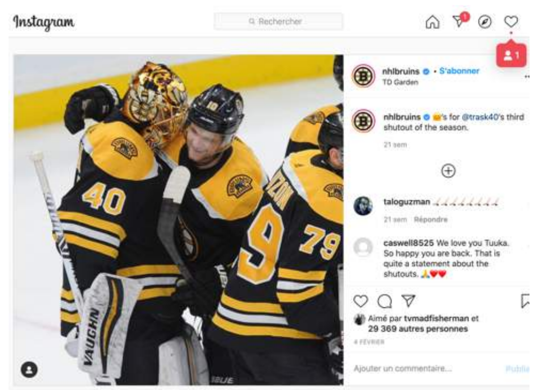
FC Barcelona



Richmond Fc

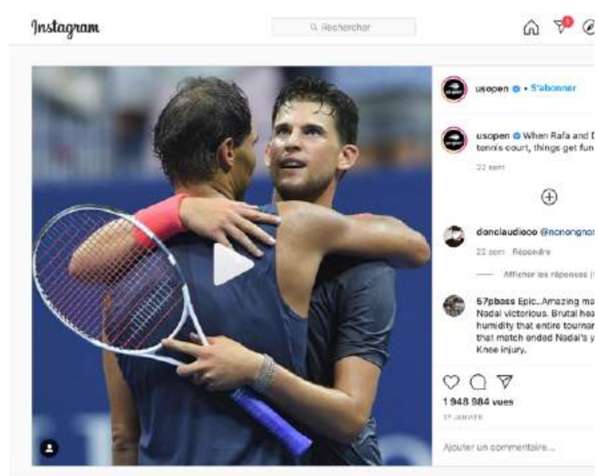


Buffalo Bruins



Manchester United

US Open



This post by Manchester United, is a case of intimacy between two friends.

A sincere hug at the end of a match between two opponents (a capture taken at the end of a video)

We decided to standardize **warm contacts such as players hugging and walking arm in arm as moments of intimacy** between players.

Behind-the-scenes :

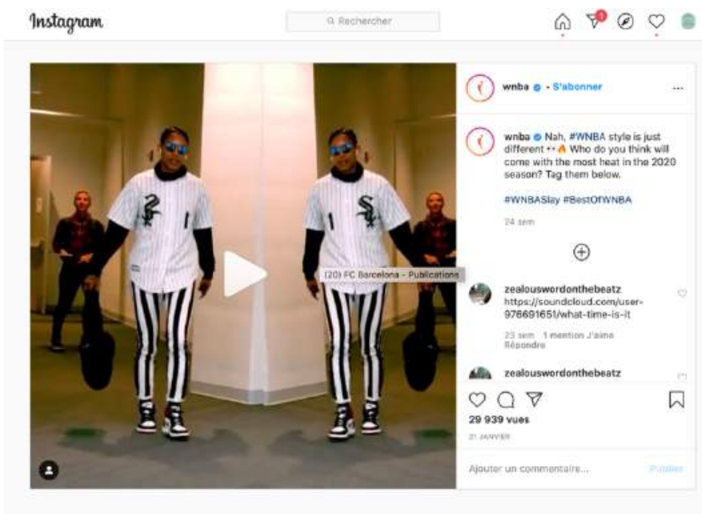
The initial reliability score for *Behind-the-scenes* is 80.9 %. *Student3* identified a significantly lower number of publications than the other two coders : 779 items for *Student1*, 641 items for *Student2*, and 123 items for *Student3*.

When we saw players **hanging out** together, talking or laughing **but not training** during practices, we would code it as *Behind-the-scenes*. If they were training – we would code it as *development*.

Arsenal : This example is textbook *Behind-the-scenes* : two players going to a practice together

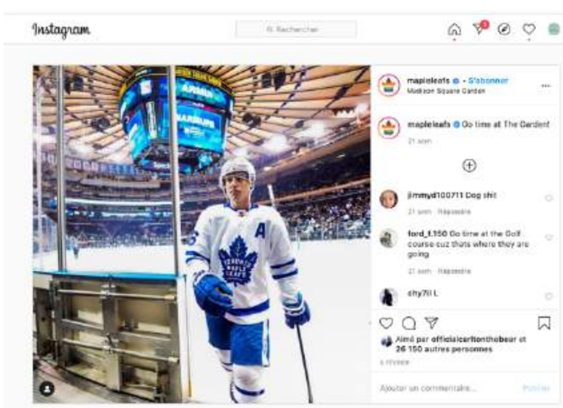
The idea of adding this category came to us after having an **exclusive access** to many basketball and hockey players photographed backstage with comments about their style.

WNBA



Other posts should be tagged ***between the scenes* or *insider's look,*** because they are not pictures taken during a performance, or "in action" but right before or afterwards.
They are not training pics, nor intimate or as clear cut as locker room shots.

Maple Leafs

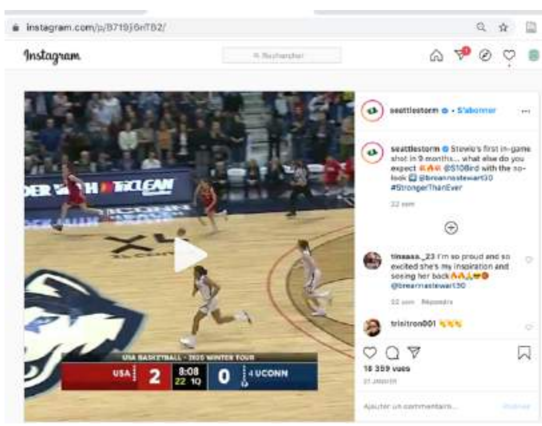


Crowdsourcing :

The initial reliability score for *Crowdsourcing* is 87.92 %. *Student3* identified a significantly lower number of publications than the other two coders : 511 items for *Student1*, 559 items for *Student2* and 75 items for *Student3*. One of the differences between *Student2* and *Student1* is that *Student2* coded under *Crowdsourcing* all **rhetorical questions,** even when they seemed to be used to emphasize a point or just to get the audience thinking.

In the example below : "*Stevie's first in-game shot in 9 months... what else do you expect 💥🔥💥 ... ",* the post doesn't really **aim at engaging consumers in the community**. It's more of a way to talk to fans to develop a sense of attachment, a sense of belonging to the same community, talking to them instead of talking at them – bonding.

Seattle Storm



Champions League

Student1 chose the posts that were really asking the consumers for an active response. We chose to go with *Student1*'s view that was more specific. Like the one from Champions League. Sometimes, to enter *Prize Draws*, customers had to vote, repost or comment. We also had to standardize all the data to make all *Prize Draws* of that type also *Crowdsourcing*.

CSR/Charity :

Charity's initial reliability score is 97.5 %. Once again, *Student3* identified a significantly lower number of publications than the other two coders : 59 items for *Student1*, 125 items for *Student2* and 19 items for *Student3*.

Again, the definition of *Charity* had two different aspects : The first one was easier to identify : "*The post brings social responsibility actions about the team/league/player. It includes investments in sustainable process, socially responsible, reusable inputs*. "

The second one however led to a bit of a disagreement : "*or if it is inviting members to play an active role in favor of social causes*". Sometimes organizations were involved with children, women, minorities for Black History Month, involved in their neighborhood, in their community but no charity organizations were clearly evoked.

Here, Wimbledon is telling the story of Althea Gibson and the importance of being a trailblazer for other black women in tennis, the social cause being equal rights and ethnic diversity.

<u>Winbledon</u>

Appendix C – Classification of Sports / Mitchell (1985)

Classification of Sports According to Mitchell (1985)

I. Intensity and type of exercise performed

A. High to moderate intensity

1. High to moderate dynamic and static demands

Boxing
Crew/Rowing
Cross-country skiing
Cycling
Downhill skiing
Fencing
Football
Ice hockey
Rugby
Running (sprint)
Speed skating
Water polo
Wrestling

2. High to moderate dynamic and low static demands

Badminton
Baseball
Basketball
Field hockey
Lacrosse
Orienteering
Ping-pong
Race walking
Racquetball
Running(distance)
Soccer
Squash
Swimming
Tennis
Volleyball

3. High to moderate static and low dynamic demands

Archery
Auto racing
Diving
Equestrian
Field events (jumping)
Field events (throwing)
Gymnastics
Karate or judo
Motorcycling
Rodeoing
Sailing
Ski jumping
Water skiing
Weight lifting

B. Low intensity (low dynamic and low static demands)

Bowling
Cricket
Curling
Golf
Riflery

II. Danger of body collision

Auto racing
Bicycling
Boxing
Diving
Downhill skiing
Equestrian
Football
Gymnastics
Ice hockey
Karate or judo
Lacrosse
Motorcycling
Polo
Rodeoing
Rugby
Ski jumping
Soccer
Water polo
Water skiing
Weight skiing
Weight lifting
Wrestling

Appendix D – Classification of sports by contact Rice (2008)

Classification of Sports According to Contact

Contact	Limited-Contact	Noncontact
Basketball	Adventure racing[a]	Badminton
Boxing[b]	Baseball	Bodybuilding[c]
Cheerleading	Bicycling	Bowling
Diving	Canoeing or kayaking (white water)	Canoeing or kayaking (flat water)
Extreme sports[d]	Fencing	Crew or rowing
Field hockey	Field events	Curling
Football, tackle	High jump	Dance
Gymnastics	Pole vault	Field events
Ice hockey[e]	Floor hockey	Discus
Lacrosse	Football, flag or touch	Javelin
Martial arts[f]	Handball	Shot-put
Rodeo	Horseback riding	Golf
Rugby	Martial arts[f]	Orienteering[g]
Skiing, downhill	Racquetball	Power lifting[c]
Ski jumping	Skating	Race walking
Snowboarding	Ice	Riflery
Soccer	In-line	Rope jumping
Team handball	Roller	Running
Ultimate Frisbee	Skiing	Sailing
Water polo	Cross-country	Scuba diving
Wrestling	Water	Swimming
	Skateboarding	Table tennis
	Softball	Tennis
	Squash	Track
	Volleyball	
	Weight lifting	
	Windsurfing or surfing	

Appendix E – Classification of sample disciplines based on Mitchell (1985)

High to moderate dynamic and static demands	High to moderate dynamic and low static demands
Boxing Cross-country skiing Cycling Fencing Football Ice Hockey Rugby Running Skating Wrestling	Baseball Basketball Ping-Pong Running Soccer Swimming Tennis Volleyball
1,5,7,9,13,15,16,17,21,23,25,26	3,6,8,18,19,20,24,27

High to moderate static and low dynamic demands	Low intensity (low dynamic and low static demands)	Danger of body collision
Racing Gymnastics Field Events Athletics	Golf Cricket	Racing Bicycling Skiing Football Gymnastics Ice Hockey Motorcycling Rugby Soccer Waterpolo
4,12,14,22	10,11,	1,4,5,7,9,12,15,16,17,26

Annexe F Summary table of all results

Table 50 *Selling* dimension on Twitter summary of all results

On all SNS	*Selling* 33,5 %	*Explicit Sell* *3,24 %*	*Implicit Sell* *30,41 %*	*Product* 3,08 %	*Price* 0,14 %	*Subscrip.* 0,88 %	*Event M.* 1 %	*Events T.* 22,74 %	*Prize Draws* 1,42 %	*Cross Promo* 12,24 %
Selling on Twitter	30,80	4,80	26,20	3,40	0,20	0,80	1	18,4	2,5	15,2
on likes	decrease									
on comments	decrease									
No body collision (%)	13,7	1,5	12,6	0,7	0,1	0,2	0,4	8,2	0,5	7,1
on likes	Decrease (higher initial CE)			decrease					decrease	
on comments										
***Body collision* (%)**	17,1	3,3	13,6	2,7	0,2	0,6	0,6	10,1	2	8,1
on likes	decrease (higher tolerance)		decrease (higher tolerance)	decrease (higher tolerance)					decrease (higher tolerance)	decrease (higher tolerance)
on comments	decrease (higher tolerance)		decrease (higher tolerance)							decrease (higher tolerance)

Table 51 *Selling* dimension on Facebook summary of all results

On all SNS	*Selling* 33,5 %	*Explicit* 3,24 %	*Implicit* 30,41 %	*Product* 3,08 %	*Price* 0,14 %	*Subscrip* 0,88 %	*Event M.* 1 %	*Events T.* 22,74 %	*Prize D.* 1,42 %	*Cross Promo* 12,24 %
Selling on Facebook	40	4,8	35,3	3,8	0,2	1,5	1,4	30,1	1,2	10,9
on likes	decrease									
on comments	decrease									
No body collision (%)	16,6	1,7	14,8	0,9	0,00	0,40	0,40	12,90	0,30	3,80
on likes				decrease						decrease
on comments	decrease	decrease	decrease					decrease		
***Body collision* (%)**	23,4	3,1	33,8	2,8	0,20	1,10	0,90	17,30	0,90	7,10
on likes				decrease						decrease
on comments	decrease (higher tolerance)	decrease	decrease					decrease		

Table 52 *Selling* dimension on Instagram summary of all results

On all SNS	*Selling* 33,5 %	*Explicit* *3,24 %*	*Implicit* *30,41 %*	*Product* 3,08 %	*Price* 0,14 %	*Subscrip* 0,88 %	*Event M.* 1 %	*Events T.* 22,74 %	*Prize D.* 1,42 %	*Cross Promo* 12,24 %
Selling on Instagram	30,2	0,5	29,8	2,1	0	0,4	0,7	20,1	0,7	10,7
on likes	decrease									
on comments	decrease (almost nil)									
No *body collision* (%)	12,1	0,1	12,1	0,5	0	0	0,4	9,4	0,3	2,7
on likes	decrease							decrease		
on comments									increase	
***Body collision* (%)**	18,1	0,4	17,7	1,7	0	0,4	0,3	10,7	0,3	8,1
on likes	decrease (less tolerance)							decrease		
on comments									decrease	

Table 53 *Quality* dimension on Twitter summary of all results

On all SNS	***Quality*** **88,2 %**	***Produc*** **0,10 %**	***Develop*** **5,28 %**	***Hooking*** **18,06 %**	***Stats*** **6,34 %**	***Immersion*** **2,92 %**	***Bridging*** **4,02 %**	***Bridg P.*** **1,66 %**	***Healthy*** **0,14 %**	***Joyful*** **30,99 %**	***News*** **25,07 %**	***Gallery*** **54,91 %**	***Highlights*** **17,48 %**
Quality on Twitter	88,3	0,2	4,4	17	6,6	1,7	4,9	1,9	0,1	27,9	35,1	48,1	15
on likes	increase												
on comments	increase						1,2	0,9	0	10,3	10,9	19,7	8
No body collision (%)	33,2	0	1,4	8	3,1	0,7							
on likes				increase			increase			increase		decrease	
on comments				increase			decrease			decrease	decrease	increase	
Body collision **(%)**	55,1	0,2	3	9	3,4	1	3,6	1	0,1	17,6	24,1	28,3	6,9
on likes				increase			increase			increase		increase	
on comments				increase			increase			increase	increase	increase	

Table 54 *Quality* dimension on Facebook summary of all results

On all SNS	***Quality* 88,2 %**	***Produc* 0,10 %**	***Develop* 5,28 %**	***Hooking* 18,06 %**	***Stats* 6,34 %**	***Immersion* 2,92 %**	***Bridging* 4,02 %**	***Bridg P.* 1,66 %**	***Healthy* 0,14 %**	***Joyful* 30,99 %**	***News* 25,07 %**	***Gallery* 54,91 %**	***Highlights* 17,48 %**
***Quality* on Facebook**	86,2	0	5,7	19,4	8,1	4,4	3,5	1,2	0,3	30,7	23,6	55	18,8
on likes	increase												
on comments													
No body collision (%)	41,70	0,00	1,40	12,90	3,80	1,90	2,40	0,60	0,30	16,60	11,80	26,90	8,20
on likes			decrease	increase	decrease		decrease			increase	increase	increase	increase
on comments	increase		decrease	increase						increase	increase	increase	increase
***Body collision* (%)**	44,50	0,00	4,30	6,50	4,30	2,50	1,10	0,60	0,10	14,10	11,80	28,10	10,60
on likes			decrease	increase	decrease		increase			increase	increase	increase	increase
on comments	decrease		decrease	decrease						decrease	increase	increase	decrease

Table 55 *Quality* dimension on Instagram summary of all results

On all SNS	*Quality* 88,2 %	*Produc* 0,10 %	*Develop* 5,28 %	*Hooking* 18,06 %	*Stats* 6,34 %	*Immersion* 2,92 %	*Bridging* 4,02 %	*Bridg P.* 1,66 %	*Healthy* 0,14 %	*Joyful* 30,99 %	*News* 25,07 %	*Gallery* 54,91 %	*Highlights* 17,48 %
Quality **on Instagram**	89,9	0,1	5,6	17,8	4,6	2,7	3,7	1,9	0	34,1	17,2	61,1	18,6
on likes													
on comments	decrease												
No *body collision* (%)	34,3	0	2,7	7,3	2,1	1,3	1,7	0,6	0	13,8	5,6	23,1	9,2
on likes				increase		decrease				increase		decrease	
on comments				increase						increase	increase	decrease	
Body collision **(%)**	55,6	0,1	3	10,4	2,4	1,4	2	1,3	0	20,3	11,6	38	9,4
on likes				increase		decrease				increase		decrease	
on comments				increase						decrease	increase	decrease	

Table 56 *Social* dimension on Twitter summary of all results

On all SNS	*Social* 40,6 %	*Bonding* 12,6 %	*Evang.* 0,06 %	*Defending* 1,82 %	*Social S.* 0,50 %	*Small T.* 1,48 %	*Intimacy* 8,16 %	*Behind the Sc.* 20,22 %	*Crowd* 11,52 %	*Charity* 2,34 %
***Social* on Twitter**	36	10,9	0	2,5	0,7	1,6	5,8	14	11,2	2,2
on likes										
on comments	increase (almost nil)	3,4	0	0,5	0,2	0,6	2,6	4,6	4,2	1,2
No body collision (%)	12,9									
on likes	decrease	increase								
on comments		decrease							decrease	
***Body collision* (%)**	23,1	7,4	0	2	0,5	1	3,2	9,4	7	1
on likes	increase	increase								
on comments		increase							increase	

Table 57 *Social* dimension on Facebook summary of all results

On all SNS	*Social* 40,6 %	*Bonding* 12,6 %	*Evang.* 0,06 %	*Defending* 1,82 %	*Social S.* 0,50 %	*Small T.* 1,48 %	*Intimacy* 8,16 %	*Behind the Sc.* 20,22 %	*Crowd* 11,52 %	*Charity* 2,34 %
***Social* on Facebook**	38,50	12,4	0,1	1,3	0,3	1,4	9,8	18,3	11,6	2,8
on likes	decrease									
on comments	decrease									
No body collision (%)	16,80	6,60	0,10	0,10	0,00	0,60	4,60	6,80	5,30	1,30
on likes		decrease								
on comments		decrease		decrease					increase	
***Body collision* (%)**	21,70	5,80	0,00	1,20	0,30	0,80	5,10	11,40	6,30	1,50
on likes		Near zero								
on comments		decrease		increase					increase	

Table 58 *Social* dimension on Instagram summary of all results

On all SNS	*Social* 40,6 %	*Bonding* 12,6 %	*Evang.* 0,06 %	*Defending* 1,82 %	*Social S.* 0,50 %	*Small T.* 1,48 %	*Intimacy* 8,16 %	*Behind the Sc.* 20,22 %	*Crowd* 11,52 %	*Charity* 2,34 %
Social **on Instagram**	46,7	14,4	0,1	1,6	0,5	1,4	8,9	27,7	11,8	2
on likes										
on comments										
No *body collision* (%)	18,1	6,8	0	0,6	0,1	0,7	3	10,1	4,3	1,5
on likes		increase						decrease	increase	
on comments	increase	increase						decrease	increase	
Body collision **(%)**	28,6	7,6	0,1	1	0,3	0,7	5,9	17,6	7,4	0,6
on likes		decrease						increase	decrease	
on comments	increase	increase						decrease	increase	