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Article

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Abstract

The present study revisits the topic of influencer marketing from a quantitative point of view. For a sample of 255 influencers from the field of women's fashion on Instagram the lists of those accounts they follow have been used to generate a network connecting them to their peers.

Based on core metrics for the influencers in the sample and the network itself, two research questions have been considered. Asking for a relative measure of the relevance of an influencer among her peer group, it has been argued that a single metric alone does not suffice. Thus, the eigenvalue centrality as a measure of an influencer's relative importance in the network of her peers is proposed complemented by the betweenness centrality as a quantitative approximation of an influencer's reach. Both concepts are shown to focus on distinctly different concepts and are used to propose a two-dimensional approach to rank influencers.

A secondary question regarding the clustering of influencers into national groups has been posed. While significant national clustering exists in the sample, so do links to influencers of different origins. Regarding cross-national links, it is particularly the highest ranked influencers that responsible for the major share of links. Nevertheless, the network of influencers in women's fashion clearly is of an internationally connected nature.

Keywords:

influencer, Instagram, women's wear, fashion, social network analysis, death of distance, social media

1 Introduction

While the term `influencer´ and the related `influencer marketing´ are relevant in the current marketing literature, the term itself is not unambiguously defined. Additionally, there is only a very limited number of publications covering the topic and providing a quantitative methodology (Arora et al., 2019; Bakshy et al., 2011; Mittal et al., 2020).

This study adds to the discussion of quantitative approaches to influencer marketing in two regards. First, it delivers an approach to quantitative influencer marketing that is based solely on Instagram

core metrics and can be used to evaluate an influencer's importance and reach in relation to their peers and without the use of any exogenously defined rating model. Additionally, the so-called death-of-distance hypothesis is considered in an influencer-related context, considering the extent of international links between influencers.

To illustrate the points raised in this study, a sample of 255 influencers on Instagram that have their primary focus on women's fashion is considered. As all influencers included in this study are women as is the population of all possible influencers, a female pronoun is used throughout the remainder of this study.

Instagram is not only a well matured Social Media platform with a broad and still steadily growing user base (eMarketer, 2020) but as well a platform that is used by most of the established influencers from the segment of women's fashion. It is a platform frequented by young users – following the numbers published by Instagram (Instagram, 2018) more than 1 billion users worldwide use Instagram with more than 70% thereof being below 35. 85% of all teens - the main clientele of tomorrow (Piper, 2019) - state that they use Instagram on a daily basis.

The segment of women's fashion has been selected as it allows to generate a large enough sample without compromising the homogeneity of the sample or the respective population, while at the same time it is restricted enough to be represented decently enough by a sample of 255.

The main research goals of this study are providing a suitable quantitative methodological approach to study the phenomenon of influencers and thereby provide decision support for marketing managers active in influencer marketing. Furthermore, it focuses on the extent by which influencers from the considered segment are connected with each other and whether distinct clusters within the network can be detected. Thus, the question is answered whether sponsored postings only reach a local clientele or whether the potential exists that influencers influence each other and thus disseminate their opinions globally.

While the literature on quantitative influencer marketing is limited, the succeeding chapter aims at providing an introduction into the topic and anchoring this study and influencer marketing in particular in the field of affiliate marketing and thus digital marketing where it originated from.

Following the review of the theoretical foundation a brief introduction into Social Network Analysis is given motivating on the one hand the methodology implemented in generating the underlying network linking the sample of influencers and on the other hand the tools required to answer the underlying research questions which are:

RQ 1: How does an approach look like that allows for a network inherent, relative ranking of influencers and their further study?

RQ 2: Are there significant links between influencers from different nationalities, or do national clusters exist within the overall network?

Following the analysis itself, the study concludes with a summary of the results and conclusions to be drawn from them, as well as research options motivated by this study and limitations linked to it. Additionally, the potential use of the results of this study for marketers involved in influencer marketing are discussed.

2 From Affiliate to Influencer Marketing

Affiliate Marketing is part of the broader field of online marketing. Companies that sell products via an online platform pay a fee to the owner of a website, a blog or a social media channel to advertise their products in different ways to generate additional sales (Lammenett, 2017).

In either case the product or service to be advertised can be provided to a 'potential' affiliate for free, hoping for positive coverage, or a contract is set up between both parties detailing the obligations and the remuneration scheme for the affiliate.

With an increasing digital change and a merging or integration of different platforms, the digital sphere and here in particular the Social Media sphere developed as a primary target of marketing activities. While Social Media has already been present for about five decades, in particular since 1997 and the introduction of Six Degrees (Boyd & Ellison, 2007). Marketing's interest in Social Media, in particular in so-called influencers – actors in a Social Media platform that have a significant followership – only rose as a relevant aspect of Social Media marketing in the last ten years (Kozinets et al., 2010).

Combining the digital equivalents of affiliate marketing and product placement with the specifics of the digital and in particular the Social Media environment and new technologies like Social Shopping results in a first definition of what is currently understood as influencer marketing. For the aim of this study this first definition of influencer marketing suffices as its focus lies primarily on influencers as actors and less on the tools to interact with them.

However, a more in-depth introduction to influencer marketing can be found in Brown and Hayes (2008) or Nirschl and Steinberg (2018). As this study focuses on Instagram influencers, Veirman et al. (2017) provide a suitable introduction to influencer marketing on Instagram. While studies like Bakshy et al. (2011), Aswani et al. (2017), Arora et al. (2019) or Mittal et al. (2020) focus on other platforms like Twitter, Aggrawal et al. (2018) on YouTube or Cavalli et al. (2011) and Arora et al. (2019) on Facebook. Arora et al. (2019) is currently the only study using a quantitative approach on Instagram data trying to quantify an influencer's importance and studying their relations. Kim et al. (2017) have a similar focus as they consider the relations between influencers, their main objective, however, lies in describing the types of links between the influencers and in particular whether linked influencers also share followers. Another Instagram-based quantitative analysis is presented by Argyris et al. (2020) who study in detail the effects of the contents of Instagram posts. Through the use of a deep-learning

algorithm, they furthermore illustrate the advantages of using machine learning approaches in the context of influencer marketing.

From a different perspective and not based on influencers' following data Haenlein et al. (2020) considers the potential and effectiveness of Instagram among other Social Media channels aiming primarily on the deduction of recommendations for practitioners. In a similar context, Jin et al. (2019) and (Jin et al., 2021) focus on the relevance of the trustworthiness of the influencer and Lee and Kim (2020) on the credibility.

However, no general and quantifiable definition of what constitutes an influencer exists, and all relevant studies define the term slightly different. A number of studies like Lim et al. (2017), Lou and Yuan (2018) or Audrezet et al. (2018) put the focus of their definitions on authenticity and the position of the influencers or their potentially large audience. On the other hand, Veirman et al. (2017) and Veirman and Hudders (2020) stress aspects like brand attitude. While terms like authenticity or brand attitude are hard to quantify, characteristics like followers, reach, posting frequency, engagement rate or growth rates are often quoted (Aggrawal et al., 2018; Bendoni, 2017; Hall, 2017) as tangible indicators of an influencers position. However, no consensus exists on relevant threshold values for these characteristics, which in consequence leads to a rather shallow distinction between nano-, micro- and macro-influencers. An additional downside of most of these studies available is that their measures are exogenously defined and do not result from the networks at hand, as is the case in Arora et al. (2019).

The definition for an influencer that is used in the course of this study and which is sufficient for all relevant purposes marks an influencer as a user of Social Media who on the platform under consideration sports at least 100,000 followers. Being termed an influencer in corresponding rankings and the relevant press adds a qualitative dimension to the used definition of an influencer. A distinction into nano-, micro- and macro-influencers does not take place as the study will focus on macro-influencers alone.

The present study aims to provide to the existing literature on influencer marketing in two ways.

The first goal of this study is to deliver a general approach to quantitative influencer marketing that is based solely on Instagram core metrics by evaluating the influencers in relation to their peers. This sets this study apart from comparable studies that evaluate influencers based on their general followership or exogenously defined scoring or rating schemes. In this regard it applies ideas as already proposed by Wu et al. (2013) and Lagrée et al. (2018) to the context of Instagram and diverges from approaches as used for example in Arora et al. (2019). Condensed into a single research question, the study tries to answer the question:

RQ 1: How does an approach look like that allows for a network inherent, relative ranking of influencers and their further study?

Second, studies like Lengyel et al. (2015) or Han et al. (2018) argue that the internet and thus a number of internet related activities like Social Media breach national borders and lead to an increasing global integration – in the literature, e.g. in the context of research and development and company cooperations this is also referred to as the death-of-distance hypothesis. This might particularly hold true for Social Media platforms, where nationality usually is not even visible. This study the revisits this hypothesis, however not on the basis of the general followership of an influencer but on the basis of her network of peers, though answering the following second research question:

RQ 2: Are there significant links between influencers from different nationalities, or do national clusters exist within the overall network?

3 Methodology and Analytical Framework

3.1 Data Source

255 influencers have been selected as a census of rankings that list the most significant influencers in women's fashion. Only those influencers were considered that additional fulfill the quantitative criterion of having at least 100,000 followers by the time of conception of the initial data set in early 2018. The rankings considered in the context of this study include Block - (Block, 2016), Collsen - (Collsen, 2016), Editorial Stuff - (Editorial Staff, 2016), Ferrari - (Ferrari, 2018), Forbes - (Forbes, 2018), Gushcloud - (Gushcloud Pte Ltd, 2017), Klein – (Klein, 2016)- and West - (West, 2017). A full list of the sampled influencers can be found in Table 7 in the appendix. This sampling method while not exhaustive incorporates an additional qualitative dimension that ensures an expert-based pre-selection. Considering the origin of the implemented rankings, a bias in the direction of US and German influencers is inevitable, but the data set as a whole can see be seen as representative for the population of influencers focusing primarily on the topic of women’s fashion.

Not for every influencer it has been tested whether and by which share they have genuine or bought followers. However, them being part of an established ranking as well as selective testing hints that almost all of them have a significant followership, validating their presence in the sample.

For each of the influencers, based on their Instagram profile, data is collected in particular on their following lists but as well on other core metrics like the number of followers, the number of other users they follow and the overall number of posts. Due to the lack of a suitable API interface, all data had to be manually downloaded from the influencers’ profiles. To assure that the collected data is not biased by time-dependent changes to the influencers’ profile all data points have been collected over the course of only two weeks.

The following lists are used to generate a directed network of links between them. The following section illustrates the involved procedure in more detail.

Additionally, external data is collected on the origin of the influencers, which other topics aside from women's fashion they cover, their age and whether they officially list receiving sponsoring or are active as a model.

All 255 influencers are women that also are active at other Social Media platform and own either a blog or their own website.

3.2 Social Network Analysis

The term 'Social Network Analysis' summarizes all those methods that can be used to model, illustrate and analyze all types of social interactions and relations in a broader context.

A social network can be seen as a set of actors that are linked in a certain way. This allows for a multi-dimensional approach with regard to the actors as well as to the type of linkages.

The simplest type of network assumes all actors or nodes in the network to be comparable, and that only a single type of linkage or edge exists between any two nodes. This is also the type of network that is considered in the course of this study.

Using this simple approach to networks makes it possible to represent the network via a quadratic matrix, where an element of row i and column j describes the relation between nodes i and j. This matrix is called the adjacency matrix.

If the network is undirected, each relation is automatically reciprocal, e.g. being friends with someone, and the adjacency matrix is symmetrical. For directed networks, a relation is not necessarily reciprocal, e.g. followings on Twitter or Instagram, and the adjacency matrix usually is not symmetrical.

While in an undirected network the in-degree, the number of links that point to a node, the out-degree, the number of links that point away from a node, and thus the degree centrality as such are identical, the situation changes in a directed network.

This study focuses on Instagram as a social network, an inherently directed network. The nodes are different actors active on Instagram, whereas the edges are the follower and following relations the actors have with each other; the in-degree is the number of followers and the out-degree is the number of other actors one follows.

The simplest way to capture an Instagram network is thus to set all elements of the adjacency matrix to zero except where actor j follows actor i, the matrix will report a 1 in row i and column j. As only the relationship network of influencers with their peers is considered, the adjacency matrix reports a 1 in row i and column j if influencer i can be found in the following list of influencer j.

A more sophisticated approach to modeling the network would be to note in element $n_{i,j}$ the number of times actor j likes or comments on a post by actor i. Aside from the additional computational burden, this would add additional levels of complexity to the analysis as following, liking and commenting

can be seen as three different dimensions that have to be treated separately. In this regard, the study focuses solely on the first type of following relations.

Furthermore, for established influencers, the in- and out-degree strongly deviate from each other. In the context of this study the in-degree, the number of followers, does not play a central role as only relations between the members of a select group of influencers are relevant here. Basing the analysis on the out-degree will achieve the same goal, but at a much lower computational burden.

While the main goal of this introductory study lies in mapping the links between selected influencers, additional measures from social network analysis like the eigenvalue centrality, the closeness centrality, the Katz centrality, the authority score or the page-rank allow for an analysis of the importance of different influencers. While this analytical approach has not yet found a foothold in the study of inter-influencer networks, studies like Wu et al. (2013) or Lagrée et al. (2018) use comparable measures to establish leaders in Social Media networks.

On the other hand, measures like the betweenness centrality or the hub score allow for an analysis of the relevance of an influencer as a potential transmitter of knowledge in the network (Newman, 2018).

With the four listed measures, first and foremost the eigenvalue centrality (as the other indicators are similar in nature and highly correlated to the eigenvalue centrality), as indicators of an influencer's relevance or importance a tool becomes available to classify influencers simply by looking at the relevance they play in the network of their peers. In the later course of the study, eigenvalue centrality will thus also be referred to as *Importance*.

Eigenvalue centrality as a concept is based on the fact that the size of an eigenvalue determines the importance of the corresponding eigenvector to generate the space containing all nodes, a concept that is implemented similarly in the context of factor analysis. Mathematically, the eigenvalues measure results from the eigenvalues of the adjacency matrix (Newman, 2018). The relevance of an influencer thus becomes network-endogenous, as compared to most qualitative studies on influencers or quantitative studies like Arora et al. (2019) that define an influencer's importance exogenously.

From a more medical point of view, Fletcher and Wennekers (2017) show for neural nets that eigenvalue centrality is correlated with the firing activity of neurons in the network, which means the introduction of new knowledge into the network; a process similar to the introduction of information via influencers. Translated into the context of Social Media networks, this means that knowledge or information introduced into the network by influencers associated with high eigenvalues will have the strongest impact on the other nodes in the network.

Simply put, influencing can be interpreted as the transmission of information from one party to another. Using the two indicators for an influencer's potential as a transmitter of knowledge or information, first and foremost the betweenness centrality (it is correlated with the other variables as well),

shows a potential of the influencer that can, at least in part, be interpreted as an approximation to her Reach among her peers.

The concept of betweenness centrality has been introduced by Freeman (1977) and is continuously updated from a mathematical-technical point. The multitude of its practical applications in the context of Social Media networks in summarized in the study by De et al. (2020). Mathematically, it is calculated as the number of times that a node lies on the shortest path between any two other nodes; in most contexts this number is then normalized to the interval [0; 1]. Since the betweenness centrality describes an influencer's potential to transmit information, it thus fulfills the same function as the concept of an influencer's reach and will thus also be referred to as an approximation for the reach in later parts of the analysis.

In this context, the approach presented herein also endogenizes at least in part the equally relevant measure of an influencer's Reach, even if not necessarily among all the followers still among the peers.

4 Analysis

4.1 Description of the Data Set

Aside from the links between the influencers, i.e. their following lists, additional core metrics have been collected as stated in section 3.1; that is the influencers' number of followers, the number of accounts they follow and the number of posts up to the point of data collection. To complement the picture of the influencers, for each one the age as far as publicly available and their origin has been collected. If any of the influencers is listed as possessing two or more citizenships the one has been used that fits the influencers center of living the best.

Table 1 summarizes the means and medians as well as minimum and maximum values for the three core metrics and the age, while *Table 2* gives an overview of the distribution of origins of the influencers in the sample.

Table 1: Central Tendency of Core Metrics

Variable	Follower	Following	Posts	Age
Mean	1,158,753	662	2,969	26.5
Median	506,000	560	2,329	28
Minimum	107,000	30	113	16
Maximum	37,900,000	4,866	17,633	40

Source: Own table

Table 2: Origin of the Influencers

Origin	USA	Germany	Sweden	Spain	Italy	UK	Australia	Russia	Netherlands	Asia*	Rest
	77	70	18	14	13	9	8	7	6	10	23

*Asia including as well China, Japan and Singapore

Source: Own table

Considering that, all four metrics in Table 1 report a mean larger than the median shows they all are rightwards skewed; they contain more small than large values. This gives rise to the assumption that even among the top influencers in the field of women's fashion, a strict hierarchy exists with very few α-influencers on top; a phenomenon that is seen again in the following analysis below. Cha et al. (2010), Weng et al. (2010) and Bakshy et al. (2011) provide evidence of similar distributions regarding Twitter networks. Perret (2021) in the context of a panel-study and underpinned by a mathematical model provides strong evidence that this structure might be endemic across Social Media, or at least Instagram.

Since the sample consists only of already established influencers - 246 have one type of professional sponsoring or another and 202 own their own blog (all of them own a blog or a personal website) – the low average age of 26.5 years, with roughly one third of the sample of an age below 25, shows that an established standing on Social Media is not as age dependent as in many offline contexts.

The majority of the influencers stem from the US (30.19%) or Germany (27.45%) as seen in *Table 2*. While other regions are represented in the sample as well, considering that it is a sample of established influencers only the large share of Germans and the small share of French (1.96%) might surprise a bit. The large share of German influencers, at least in part, is due to the fact that some German influencer ranking have been used to build the sample.

To get a better feel for the data, it has been considered how the core metrics relate to each other. The number of followers that is usually considered the central figure in quantitative influencer marketing does not correlate significantly with any of the other three metrics. The correlation coefficient by Pearson and Bravais is r = -0.0157 for the followed, r = 0.0873 for the number of posts and r = -0.0507 for the age. All three aspects thus cannot be considered central impact factors on an influencer's relevance, if it is measured via her followers, which questions the usability of the followers as the single measure of relevance.

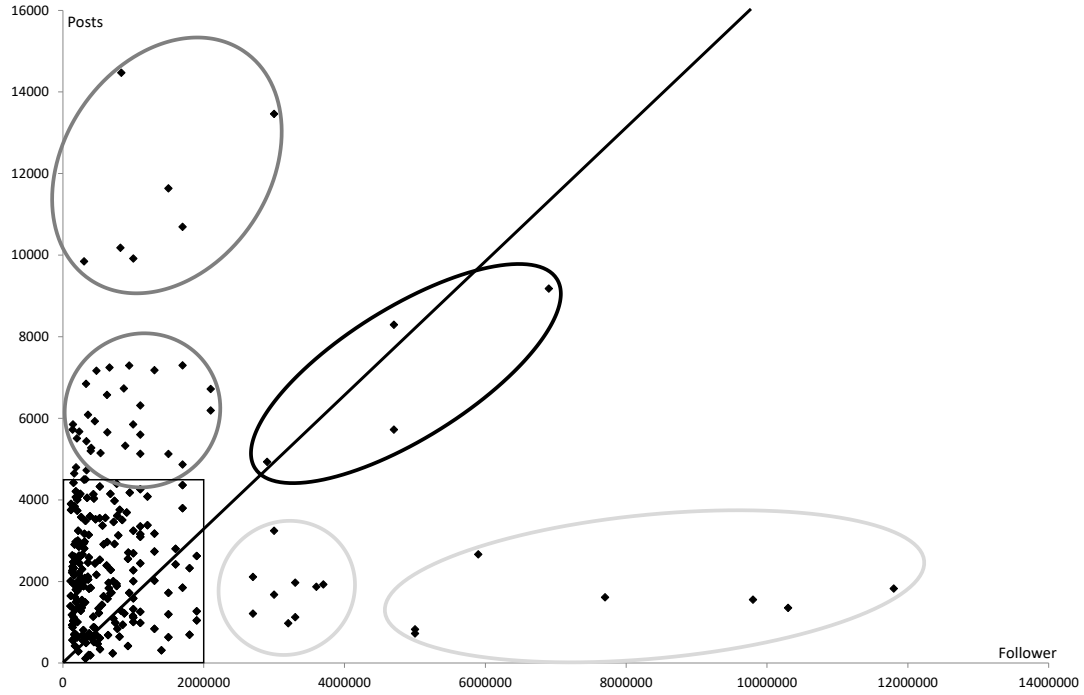

Figure 1: Followers vs. Posts
Source: Own figure

An additional interesting insight can be generated if follower numbers and posts are plotted against each other, as done in *Figure* 1.

The figure clearly shows that four more or less distinct groups exist. In the upper left area, the two dark gray ellipses describe over-performers who post comparatively much as compared to the under-performers in the lower right area. From a different perspective, the dark gray area could also be referred to, as those influencers that use a quantity-oriented approach to posting whereas the influencers on the lower right rather use a quality-oriented approach to posting.

The black ellipse in the middle shows those influencers who reach a relative equilibrium. However, the black box in the lower left is of particular interest since it contains roughly 80% of all influencers and those contained within show no relation of any type with a correlation of just r = 0.000 (p-value = 0.997). Note, that all stated correlations are rank correlations, since all considered variables are significantly different from a normal distribution.

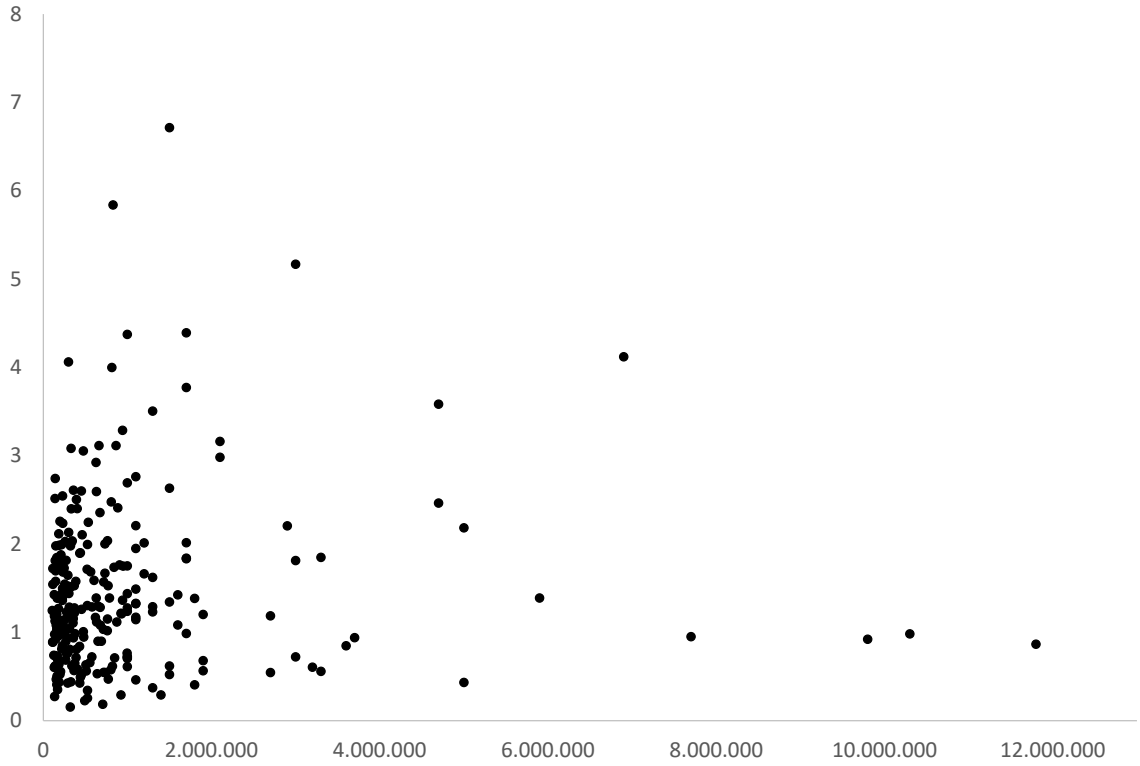

Figure 2: Followers vs. Posting Frequency
Source: Own figure

A comparable pattern can be observed for any combination of the metrics followers, followed and posts. In addition, the pattern only marginally changes if the number of posts is replaced by the average posting frequency – the number of posts divided by the time active on Instagram – taking into account that long-term members had more time to accrue posts. *Figure* 2 illustrates this relation – excluding Gigi Hadid with 37.9 Mio. followers and Arielle Noa Charnes with an average posting frequency of more than 45 posts per day. While the under- and over-performers became harder to be identified, the majority of influencers can still be found in a rather bounded area in the lower left of the figure.

Accounting for an influencer´s age in physical as well as in digital form is an important aspect to avoid biases in general, but major patterns still remain even if they are no longer as distinct. While the internet in general and Social Media in particular facilitate fast growth of certain persons' prominence, a longer time horizon in which they can actively work on their prominence and their image might increase just that. This argument is supported by a strongly significant ($p = 0.000$) positive correlation of $r = 0.631$ between the number of posts of an influencer and days active on Instagram. With a correlation of $r = 0.5310$ (p 0.000) the relation between physical age and posts is only marginally less pronounced.

4.2 A new approach for a network inherent, relative ranking of influencers

Applying the approach laid out in section 3.2 to the data set introduced in section 3.1 resulted in a network with 251 of the 255 influencers being linked to at least one other influencer. The four influencers that do not integrate into the network are Naomi Neo, Federica Nagi, Carly Heitlinger and Ivania Caprio.

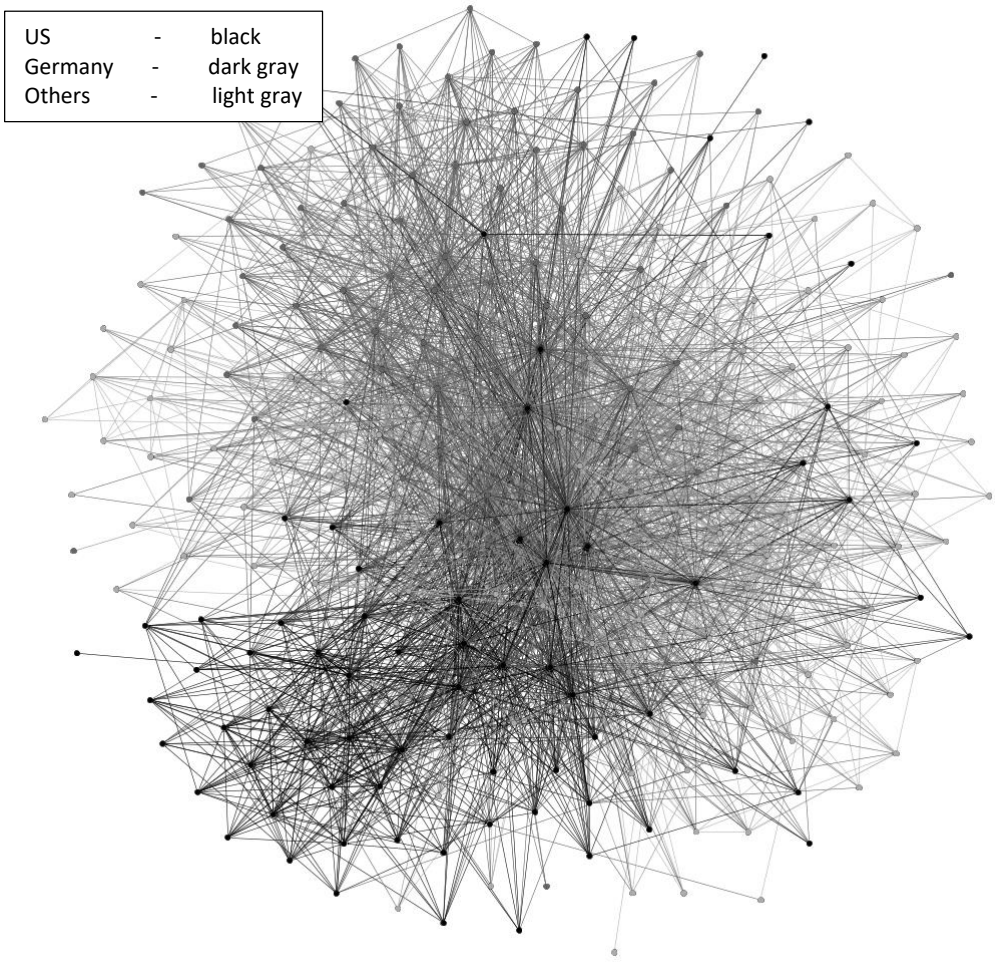

Figure 3: Influencer Network – Origin-based Coloring
Source: Own figure

The nodes / influencers in the network and the corresponding linkages / followings are color coded with influencers stemming from the US being black, those from Germany being dark gray and all others being light gray.

Figure 3 shows that while a distinct black and dark gray cluster exist, there are a number of ties between differently colored nodes. This gives rise to the second research whether in the context of Instagram influencing nationality plays a role when following another influencer.

Following the comment at the beginning of this section that only four influencers from the sample are absent from the network, the figure additionally shows that there also are only very few influencers with only one or two links to the network.

In total there are only five influencers in the data set with an out-degree of zero – excluding the four that are not part of the network, this leave only one in the network who does not follow any of the other 254 influencers. Excluding these five influencers, the average out-degree is 14.528 with a median of 13. The in-degree perspective, however, looks quite different and considerably more concentrated, with only 111 influencers having an in-degree of more than zero. The average in-degree of those that are different from zero is 32.7207 with a median of 22. This shows that even in this set of top influencers the major focus is concentrated on only a select few which in the previous section were termed α-influencers. It also shows that α-influencers are actually well-known to their peers and relevant to them as well.

Table 3: Best connected Influencers worldwide (by degree-centrality)

Name	Origin	In-Degree	Out-Degree	Degree Centrality
Ohhcuture (Leonie Hanne)	Germany	144	40	184
Songofstyle (Aimee Song)	USA	128	27	155
Chiaraferragni (Chiara Ferragni)	Italy	130	24	154
Weworewhat (Danielle Bernstein)	USA	80	58	138
Gighadid (Gigi Hadid)	USA	130	1	131
Milenasecret (Milena Karl)	Germany	62	38	100
Camilacoelho (Camila Coelho)	Portugal	77	15	92
Peaceloveshea (Shea Marie)	USA	67	23	90
Garypeppergirl (Nicole Warne)	Australia	74	11	85
Angelicablick (Angelica Blick)	Sweden	69	16	85

Source: Own table

Table 4: Most followed Influencers worldwide

Name	Origin	In-Degree
Ohhcuture (Leonie Hanne)	Germany	144
Gigihadid (Gigi Hadid)	USA	130
Chiaraferragni (Chiara Ferragni)	Italy	130
Songofstyle (Aimee Song)	USA	128
Taylor_hill (Taylor Hill)	USA	80
Weworewhat (Danielle Bernstein)	USA	80
Oliviapalermo (Olivia Palermo)	USA	79
Camilacoelho (Camila Coelho)	Portugal	77
Angelcandices (Candice Swanepol)	South Africa	75
Garypeppergirl (Nicole Warne)	Australia	74

Source: Own table

Considering that 111 of 255 (43.53%) report an in-degree of more than one shows that the sampling of influencers introduced in section 3.1 is suitable. A significant share of the sampled influencers is considered relevant even among their peers.

Table 3 and *Table 4* summarize the best-connected actors by considering the overall degree centrality as in-degree plus out-degree and the most followed influencers measured via the in-degree. While some influencers appear in both tables, the match is not perfect. This is witnessed as well from a Spearman rank correlation coefficient of 0.774 between the in-degree and the degree centrality. The presence of a number of Germans among the top of these lists validates as well their strong presence in the overall data set.

From a practical point of view, this means that while a strong relation exists between the well-connected actors in a network and those that are followed strongly by others, this link is not perfect. Thus, an importance indicator that is built upon the overall structure of the network will provide additional important insights, while a view based solely on follower numbers cannot.

Building on the introduction to Social Network Analysis in section 3.2 the eigenvalue centrality and the betweenness centrality as measures or approximations of an influencer's importance and reach have been calculated. With all influencers plotted into a diagram for the Importance and Reach scores, *Figure* 4 results.

Compared to the diagrams in *Figure* 1 and *Figure* 2 it is no longer possible to make out particular clusters, but different layers can be conceived. Calculating Spearman correlation coefficients (both indicators are strongly non-normal) reveals that there is a strong correlation of $r = 0.940$ ($p = 0.000$) between

the two variables. However, most of this relation stems from the fact that more than 150 influencers report a score of 0 in both indicators. The correlation drops to r = 0.543 (p = 0.000) if these cases are excluded. Nevertheless, in either of the two cases a Cronbach's α of 0.085 or 0.082 respectively (excluding the zero cases) reveals that both variables describe significantly different concepts.

Considering the depiction of the two indicators as in *Figure* 4, the outer layer consists of Danielle Bernstein, Leonie Hanne, Chiara Ferragni, Aimee Song and Gigi Hadid, whereas the second layer would be Nicolle Ciotti, Milena Karl, Nicole Warne, Candice Swanepoel and Taylor Hill.

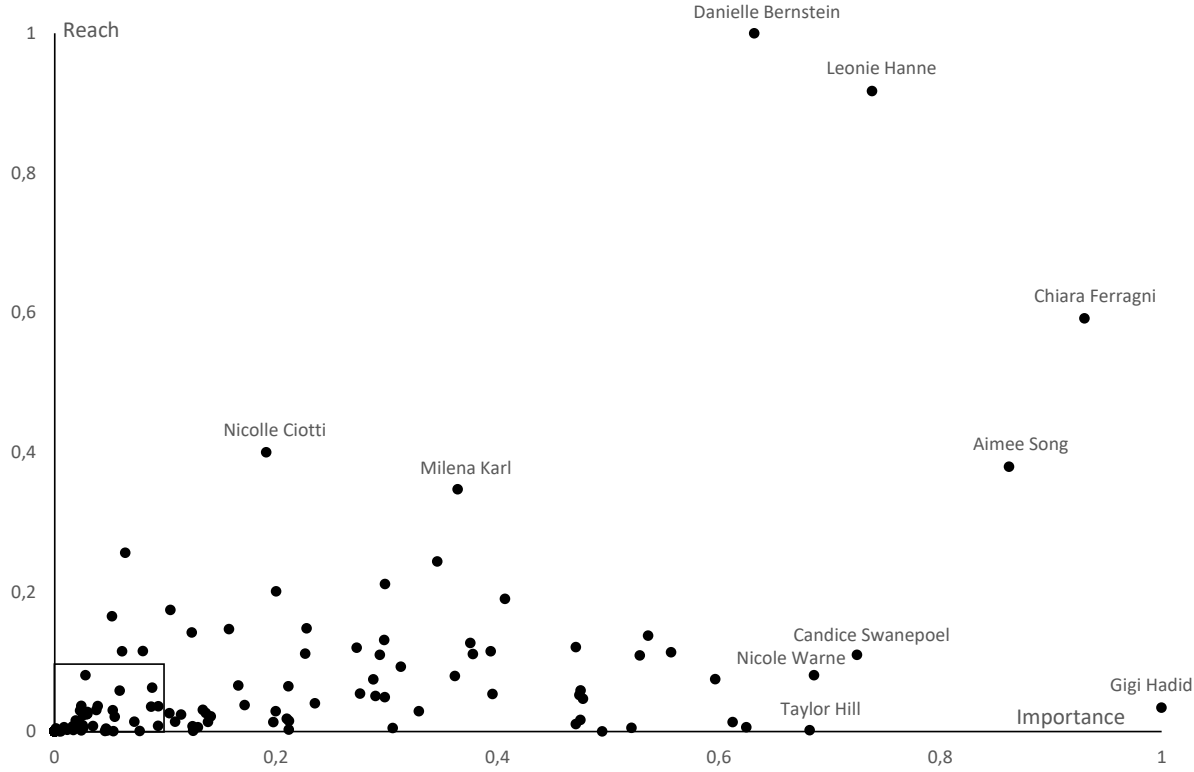

Figure 4: Influencers' Importance and Reach
Source: Own figure

This again motivates the idea of α-influencers. The box in the lower left is bounded by an Importance and Reach score of 0.1, and similar to the box in *Figure* 1 captures roughly 80% of all influencers with the majority of them (154 in total) being situated at a score of zero – which is achieved instantaneously if the in- or out-degree is zero.

A differentiation into α-, β- and γ-influencers might thus be a helpful classification. The box in the lower left then contains γ-influencers. The gammas play almost no role at all in the network, while, however, still being a part of it. The β-influencers are somewhat relevant in the network and would be all those not explicitly mentioned by name. Finally, the α-influencers are clearly dominating not only in regard to their followers in general, but as well in regard to their peers. While the distinction of actors in a

network into particular roles in considered in some studies on Social Media like Havakhor et al. (2016) in the context of influencers and in particular fashion influencers, no such study exists at this point.

4.3 International Links between Influencers vs. National Clusters

Since Figure 3 already illustrates the international relations of the influencers, in this section the focus lies on determining the magnitude of these relations.

Table 5 together with an average number of links of 28.94 more or less implies that except for the US and Germany, influencers with a different origin need to integrate internationally to become a relevant player in the network.

Table 5: Top 5/6 most followed Influencers in Germany and in the US

Germany			USA		
Name	In-Degree National	In-Degree International	Name	In-Degree National	In-Degree International
Stefaniegiesinger (Stefanie Giesinger)	54	65	Songofstyle (Aimee Song)	45	128
Ohhcuture (Leonie Hanne)	46	144	Somethingnavy (Ariell Noa Charnas)	40	67
Novalanalove (Farina Opoku)	41	54	Thriftandthreads (Brittany Xavier)	37	62
Pamela_rf (Pamela Reif)	39	55	Gigihadid (Gigi Hadid)	36	130
Milenasecret (Milena Karl)	37	62	Blankitinerary (Paola Alberdi)	33	58
Matiamubysofia (Sofia Tsakiridou)	37	53			

Source: Own table

Focusing thus on the US and Germany in particular, Table 5 summarizes the number of followers the top-influencers have that share the same origin vs. how many followers they have in total among their peers worldwide.

While it is not incidental that many of the reported names coincide with the names already mentioned in the previous section in the discussion of *Figure* 4. It is interesting to note that for all of them there is a discrepancy between the international in-degree, being in three cases almost up to three times as high as the national one. This clearly strengthens the impression already obvious from *Figure* 3 that significant international linkages exist between the top influencers.

Combining the results with those from *Figure* 4, however, seems to indicate that the degree of international activity is not strongly linked to an influencer's position, her relevance in the network of her peers. Influencers can thus become important players locally as well as globally - positions that in Social Network Analysis are called local and hidden champions.

If this analysis is expanded to encompass the whole dataset and the overall number of links between influencers Table 6 results. The first entry in each cell marks the absolute number of links between

influencers of the respective country combination. Considering that the sample contains differing numbers of influencers for each of the three origins, the numbers were adjusted by division with the number of influencers of each of the two countries (For illustrative purposes the results are multiplied by a factor of 100 afterwards). Before adjustment, a Cramer's V of 0.3246 results and afterwards of V = 0.3397. In either case, indicating a strong relation and thus a pronounced structure contained within the dataset.

Table 6: Links between influencers of different origins

		Influencer from…		
		USA	Germany	Rest of World
follows influencer from	USA	665 11,2161	149 2,7644	291 3,4993
	Germany	250 4,6382	649 13,2449	319 4,2196
	Rest of World	413 4,9663	257 3,3995	639 5,4784

Source: own table

While influencers from the rest of the world are mostly independent of their choice of whom to follow – which might also be due to the fact that it encompasses a number of countries – for the USA and Germany a distinct home-bias can be observed. Nevertheless, for the USA about half of the links go abroad, while for Germany it is almost 40%. This clearly indicates that links between influencers are not bound by national borders. However, if the numbers in Table 6 are compared to those in Table 5 it can also be seen that it is mainly the top influencers previously termed α influencers that drive the process.

Going back to section 3.1 and the sample of influencers used in the course of this study. It has been criticized that the list of selected influencers favors the US and Western Europe, excluding significant parts of Asia, the Middle East, South America and Africa. While the sample originates from lists of internationally relevant influencers, it is prudent to assume that a significant share of locally very successful influencers might have been left out of the sample. Thus, the 80-20 rule might hold in this context as well, assuming that this study only focuses on the globally well-known influencers and thereby excludes 80% of influencers that only matter as local champions. Incorporating local champions as well however would require a comparative in-depth analysis of a number of local Social Media spheres and will not be part of this study. Considering Twitter, Bakshy et al. (2011) provides evidence that leads to suspect that a share of 80% of influencers that only enjoy local relevance might indeed be a phenomenon across multiple Social Media platforms. In either case, the bias would only shift the focus of this study from influencers in general to the major influencers of international renown.

While the insight that top influencers are internationally linked might not be big news to anyone active in Social Media Marketing, this study shows it quantitatively and measure its extent on a comprehensive if not fully exhaustive basis for the women's fashion sector, a significant sector in Social Media influencing.

5 Conclusions, Limitations and Outlook

5.1 Summary

In the present study, data for 255 influencers from the field of women's fashion has been considered to gain new insights for quantitative influencer marketing on Instagram. Additionally, the network among the sampled influencers has been used to generate new indicators that can be implemented to determine the relevance or importance of influencers not solely in regard to their followers but in particular in regard to their peers. While this idea in itself is not new (Havakhor et al., 2016) this study provides to the discussion in two ways.

The first research question considers how a network-inherent ranking of influencers (section 4.2) as compared to one based on an exogenously given rating scheme can be developed. Aside from Havakhor et al. (2016) (e.g. betweenness centrality) who also implemented some network-inherent indicators other studies use evaluations of influencers that result from exogenously defined importance measures (Aggrawal et al., 2018; Arora et al., 2019; Mittal et al., 2020). Second, due to severe restrictions in the Instagram API current studies focus mostly on Twitter (Arora et al., 2019; Bakshy et al., 2011; Cha et al., 2010; Mittal et al., 2020; Weng et al., 2010), YouTube (Aggrawal et al., 2018) or Facebook (Arora et al., 2019; Cavalli et al., 2011) and Instagram as a Social Media platform with its peculiarities remains severely under researched except as part of the study by Arora et al. (2019). Third, many of the studies focus on the functionality of their approaches and marketing or sectoral points of interest are considered secondary at best. In contrast, this study implemented a well-constructed sample to offer insights into the field of women's fashion (section 4.1).

Based on the extracted network eigenvalue and betweenness centrality, two orthogonal measures, are introduced and shown to contribute to the description of an influencer's importance and reach (second part of section 4.2). Using the distribution of the influencers in accordance to these two indicators allows differentiating between α-, β- and γ-influencers (based on the statistics as summarized in *Figure* 4). A distinction that shows which influencers have a significant impact not only on their followers but on their peers as well, versus those that only matter with regard to their own followers. *Figure* 4 illustrates the distribution of influencers and makes that the α-influencers are far superior in both regards of importance and reach whereas the γ-influencers do not matter at all in the network of their peers. This result expands the study by Havakhor et al. (2016) and as well the one by Mittal et al.

(2020) who both argue that at least a combination of core metrics is required to determine an influencer's relevance. Bakshy et al. (2011) additionally stresses that in addition to the current relevance of followers, it is their past relevance that matters as well; an aspect that in this study is covered by the eigenvalue centrality since a well-established position in the network can only be the result of previous work and its acceptance by their peers.

The second research question asked about the links between influencers and whether the influencers based on their origins are nationally segregated or whether nationality does not play a relevant role. Building on the constructed network of following relations, the extent of nationality-based clustering has been studied. It has been shown that while a bias to link to influencers from the same country of origin – more pronounced in Germany than in the US – is present as witnessed by a Cramer's V of 0.3397 there still exist a significant number of international links that allow to argue that in particular the top influencers (as in α and β influencers) are globally well integrated.

These insights complement the arguments by Lengyel et al. (2015) and Han et al. (2018) that the death of distance hypothesis potentially holds for Social Media platforms in general or Instagram in particular, but surely does so for the sub-group of top influencers in this particular field of study.

The study thus provides additional inputs for marketing practitioners active in the field of Social Media marketing that are looking for additional inputs or suitable metrics to evaluate the relevance of the influencers or affiliates they cooperate with.

5.2 Conclusions for Practitioners

While there already exists software packages that focus on quantitative aspects of influencer marketing, these packages regularly only focus on the performance of one particular influencer evaluated against a previously determined set of metrics. The focus on only a single influencer, usually the one being managed by the user of the respective software solution, is due to continuous changes to Instagram's API that increasingly preclude the automatic access to most data except for a personal account – similar argument although on a lesser scale hold for other Social Media platforms as well. Platforms that offer cross-sectional data on influencers like Phlanx are limited in their scope on a report of core metrics.

While the logic behind using the core metrics implemented in most software solutions still in existence cannot be criticized this type of approach offers only absolute metrics and thus an absolute frame of reference. A relative perspective, however, is at least of equal importance. This study has shown that using a relative approach to influencer marketing allows for a much more multi-facetted perspective and it allows for a quantification of the previously rather qualitative measures of importance and reach. Thus, using the proposed procedure and the deduced modes of analysis detailed in the context of the first research question, a comparative study and thus a comparative evaluation of influencers is possible and can add an important quantitative dimension to the evaluation of an influencer's value.

Additionally, the two measures do not require an exogenously determined scoring model but provide information on the influencers based on their position in the network of their peers alone.

The present study delivers a first evaluation of the most relevant influencers in the field of women's fashion to be used by practitioners from this field. It also offers a first quantitative analysis indicating that importance and reach not necessarily coincide but offer two distinctly different points of view, even if approximated by eigenvalue and betweenness centrality. Thus, the study motivates to differentiate influencers (which at this point implies top influencers) into two or potentially three groups – α-, β- and γ-influencers. Cooperation with an α-influencer will add the bonus that the influencer's posts not only reach her direct followers, but might generate compound multiplier effects by influencing other influencers as well. This compound effect of top-level influencers could additionally be used as a measure of an influencer's value.

Thus, the results of this study provide valuable insights for companies as well as for influencers themselves. Companies trying to evaluate influencers they are planning to cooperate with have a multifacetted tool to identify sets of suitable partners while influencers can evaluate their own worth, their potential rivals and establish a better, more scientifically founded bargaining position.

Considering that the death-of-distance hypothesis holds for in particular for α-influencers adds to the practical relevance of the arguments given above since α-influencers not only have a multiplying effect by influencing other influencers, they also reach a more international audience. Thus, applying the indicators introduced herein will give a company a perspective on areas that will be particularly impacted by this multiplier effect. It will thus alleviate the selection process of the right influencer for a particular campaign.

5.3 Limitations and Outlook

This study is limited to the data present for a single year. In this regard, it has not been possible to study dynamics influencing the network constructed herein. It was thus not possible to ascertain that the results of the study hold over time.

Additionally, the field of women's fashion has been selected because it already is a developed field with a number of actors that allow for a broader analysis. Working with a network that can be considered fully developed has the problem that the development path that lead to the situation as captured in this study can no longer be studied in more detail. Aside from expanding the regional perspective of this study or its focus, the question can furthermore be raised whether the results can be extended to other sectors or Social Media platforms.

The study focused on a sample of globally active and well-known influencers and can be considered as suitably representative. Nonetheless, a number of locally relevant influencers from South East Asia, Africa, the Middle East and in part Southern America might have been excluded as they do not appeal

to a global audience. While this does not impact the validity of the findings in this study, it might provide additional research incentives and raises the question of what makes a locally relevant influencer become globally relevant.

An additional question of particular interest is whether and to which extent the international links in the network form at the beginning of an influencer's career, or whether established influencers when they enter a new medium first develop a national followership or transfer their previously active followership from an old medium into the new one. In a similar direction, the question can be raised whether the development path of an influencer and their integration into the network of peers is different if they enter Instagram as their first and primary medium or when they already established themselves on a different platform.

In the analytical part, it has already been established that some core metrics of an Instagram influencer are correlated while others clearly are not. The question can thus be asked whether building on the core metrics and the resulting network of peers, a comprehensive model explaining the importance of an influencer can be constructed.

Appendix

Table 7: List of Sampled Influencers

_thefab3	courtney_shields	janicejoostema	mariapombo	sarah.harrison.official
by.iris.sophia	cribuccino	janinapfau	marieserneholt	sassyredlipstick
annelaurenmais	darya	janinauhse	marinathemoss	sav.labrant
adriannasf	darylanndenner	jannid	martacarriedo	scarlettgartmann
alexachung	designdschungel	jeannedamas	martapozzan	seewantshop
alexis.belbel	desiperkins	jeennny____	maryanaro	serlinahohmann
aliciastylish	dianazurloewen	jordanunderwood	masha	shantijoantan
alwaysjudging	dominokati	josefinehj	mathildegoehler	si_sichen
alyson_haley	donnaromina	jourdansloane	matiamubysofia	sierrafurtado
amberfillerup	double3xposure	juelimery	mattssonmoa	sincerelyjules
anajohnson	dreachong	juleslw	mayastepper	sistinestallone
andreabelverf	dressupbuttercup	juliahengel	melinasophie	sivanayla
andreaviktoria	ebbazingmark	julialundinblog	melissackoh	sofiarichie
angelcandices	lyss	junesixtyfive	melissasatta	ariellecharnas
angelicablick	ele.rc	kateymcfarlan	michelletakeaim	songofstyle
anna.wilken	elenacarriere	katharinadamm_official	mikutas	sonyaesman
annamariadamm	eleonoracarisi	kathleen_barnes	milena.karl	sophiachong
annatatangeloofficial	ellabrooksblog	kbstyled	miss_gunner	sophieelkus
anniju__	elle_ferguson	kenzas	missalena.92	spanglishfashion
anuthida	emaxlouise	kimhnizdo	missysueblog	stefaniegiesinger
ashleyrobertson	emilyanngemma	kisu	mollyrustas	stuartbrazell
aspynovard	emilyvartanian	laurabeverlin	mvb	styledsnapshots
aylin_koenig	emitaz	lauraescanes	naomineo_	stylescrapbook
belenhostalet	emmaroseofficial	laureen	nastilove	susiebubble
belluspuera	esmirnatapia	Laurenelizabeth	natasupernova	tammyhembrow
bettyautier	estefaniac2t	laurenkaysims	nhitastic	tatjanamariposa
bettytaube	euniceannabel	lenagercke	nicholeciotti	taylor_hill
biancabrandolini	fannylyckman	lenaperminova	nicolefalciani	teresaandresgonzalvo
biancaingrosso	fashiioncarpet	lenaterlutter	nicolettemason	thassianaves
black_palms	fashion_jackson	leomieanderson	ninalaureen	thebeautybeau
blaireadiebee	fashionedchicstyling	limaswardrobe	ninasuess	thefashionguitar
blankitinerary	fata.hasanovic	lindatol_	ninauc	themrsgibby
bonniestrange	fede_nargi	linnahlborg	kayla_seah	brittanyxavier
camilacoelho	gabifresh	lisa.olssons	novalanalove	tonigarrn
camillecharriere	galagonzalez	lisadengler	leoniehanne	tonyamichelle26
caraloren	nicolewarne	lisamarie_schiffner	oliviapalermo	trendy_taste
carina	gigihadid	lizkaeber	pamela_rf	valentinapahde
carlotaweberm	gypsea_lust	lolariostyle	pandorasykes	vallibeatrice
carly	hannalicious	lornaluxe	patriziapalme	vanessafuchs
carmushka	hauteofftherack	love_aesthetics	pau_eche	vickyheiler
caro_e_	helenowen	alexandrapereira	sheamarie	victoriatornegren
carodaur	christineandrew	luanna	pernilleteisbaek	vivaluxuryblog
celinebethmann	howimetmyoutfit	lucywilliams02	phiaka	walkinwonderland
champagneandchanel	iluvsarahii	luisalion	ploychava	wendyslookbook
charlottebridgeman	imjennim	lydia.webb	queenofjetlags	wethepeoplestyle
chiarabiasi	ischtarisik	lydiamillen	rachparcell	weworewhat
chiaraferragni	itscaroo	majawyh	rocky_barnes	xenia
chrisellelim	itziaraguilera	marenwolf	rosielondoner	xeniaadonts
claudiaalende	ivanikolina	jennycipoletti	rozalia_russian	xlaeta
cmcoving	jaceyduprie	mariafrubies	salinachai	yvonnepferrer
collagevintage	jaglever	mariakragmann	sannealexandra	zorannah

Source: Own table

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