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Rainer Olbrich/Patrick Bormann/Christian Holsing

**Controlling and Evaluating Affiliates
– an Exploratory Research in the Education Sector**

MAR KET ING

FernUniversität in Hagen

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Preface of the Authors

Affiliate marketing describes a form of cooperation between two participants, conducted through the Internet. This cooperation generally starts when a merchant searches for affiliate websites. A successful search produces an agreement to cooperate, such that affiliate websites promote the merchant's products or services to consumers through digital advertising, in exchange for a commission.

Cooperation between merchant and affiliate

The main advantage comes from the availability of more exact tracking of user actions compared with classical banner advertising. Banner advertising from the late 1990s entailed clicks on an ad; affiliate marketing offers a means to track leads and then sales too. A lead represents user-specific requests for information, signaling interest in a product or service. A sale means the actual purchase of a product or contract for a service.

Advantages of affiliate marketing

But controlling and evaluating affiliates remains an ongoing, never-ending job that can take up most of marketing managers' time and efforts. Some managers, faced with the overwhelming task of evaluating vast digital sales forces of affiliates, rate affiliates solely on key performance indicators (e.g., clicks, leads, sales). Ignoring the power of pre-economic behavior though (e.g., strong social media activity) likely distorts the effectiveness of this evaluation process, potentially excluding some highly profitable affiliates.

Emerging problems in affiliate marketing

We seek to understand the affiliate marketing process in detail by identifying and grouping affiliates' pre-economic behavior, both on their own websites and social media channels, before analyzing some key performance indicators. In addition, we address users' perceptions of advertising channels and their influence on affiliate marketing.

Aim of the study

Hagen, July 2016

Univ.-Prof. Dr. Rainer Olbrich

Dipl.-Ök. Patrick Bormann

Dr. Christian Holsing

Overview of the research results

Chapter 1. Controlling and Evaluating Different Affiliate Types

- It is rare for academic research to include data from multiple affiliate networks and social networks.

Chapter 2. Literature Overview on Affiliate Marketing

- Several topics have been examined in prior literature: trust, the impact of network size on search engine rankings, perceived usefulness of affiliates, moral hazard, episodic complementary goods, product complexity, and involvement.
- Remaining issues include social networks, different affiliate types, and the focus of affiliate websites.

Chapter 3. Data Analysis and Clustering Approach

- Affiliates use text ads more often than banner ads. Search engines dominate perceived advertising channels **(Descriptive Results 3.3)**.
- If the website focus of an affiliate is thematically unlike the offer of the merchant, nearly all the social activity of the affiliate is high **(Clustering Approach 3.4)**.
- Affiliates with the most ads, most social activity, and most clicks and leads do not behave as expected; for example, they do not achieve many sales **(Clustering Approach 3.4)**.

Chapter 4. Discussion

- Clusters with many affiliates do not necessarily achieve better key performance indicators. For example, the largest cluster of thematically related affiliates has no more sales than a thematically unrelated cluster.

Chapter 5. Conclusions

- Merchants should work with affiliates that exhibit different focuses in their thematic websites **(Managerial Implications 5.1)**.
- Merchants could work together with affiliates that use social networks, though with this approach, competition increases for the merchant **(Managerial Implications 5.1)**.
- Further research should consider affiliates' business models, users' recommendation behavior, users' navigation, the behaviors of fraudulent affiliates, consumer goods settings, and other payment models **(Limitations and Further Research 5.2)**.

1. Controlling and Evaluating Different Affiliate Types

Affiliate marketing has grown to touch nearly every form of digital marketing because it is easy to establish and in most cases involves a low risk.[1] This marketing method generally starts with a merchant in search of various affiliate websites. These affiliates promote the merchant's products or services to consumers through the Internet with digital advertisements.[2] Furthermore, affiliate websites maintain varying business models, such as blogs or communities to inform about and recommend users different products and services.[3] To enhance the utility of their business models, affiliates often rely on product lists or voucher codes that feature links to the merchants' sales channel.[4] If the merchant outsources search of affiliates together with payment and tracking of transactions, it can use affiliate networks to regulate these processes.[5] Estimates suggest that affiliate marketing spending reached $1.5 billion in Europe in 2013[6] and that U.S. spending will reach $4.5 billion by 2016.[7] Largely, this development is driven by financial service providers, retailers, and online education providers.[8]

Merchant and Affiliate

Figure 1 shows a typical affiliate marketing process from a merchant's perspective.[9] A user starts by visiting an affiliate website and potentially clicking on a digital ad. With this click, the affiliate redirects the user to the merchant's website. To request more information about the merchant's services or products, the user fills out a form and receives an e-mail in response, with further documentation (lead). Subscribing to a service contract or buying a product constitutes a sale.

Typical affiliate marketing process

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[1] C. f. BROWN 2009; FIORE/COLLINS 2001; GOLDSCHMIDT/JUNGHAGEN/HARRIS 2003; HOFFMAN/NOVAK 2000.

[2] C. f. DUFFY 2004, 2005; HELMSTETTER/METEVIER 2000.

[3] C. f. MARKETING SHERPA 2007, HERRING ET AL. 2005; HOLLENBAUGH 2011; KOZINETS ET AL. 2010; PRUSSAKOV 2011.

[4] C. f. OLBRICH/HOLSING 2011; PRUSSAKOV 2011.

[5] C. f. GOLDSCHMIDT/JUNGHAGEN/HARRIS 2003.

[6] C. f. IAB 2012, 2013, 2014.

[7] C. f. FORRESTER RESEARCH 2012.

[8] C. f. PRUSSAKOV 2009.

[9] Solid ellipse indicates the actual payment model for the merchant. If a user subscribes to the service, it constitutes a sale, but the affiliate would receive no commission for this subscription.
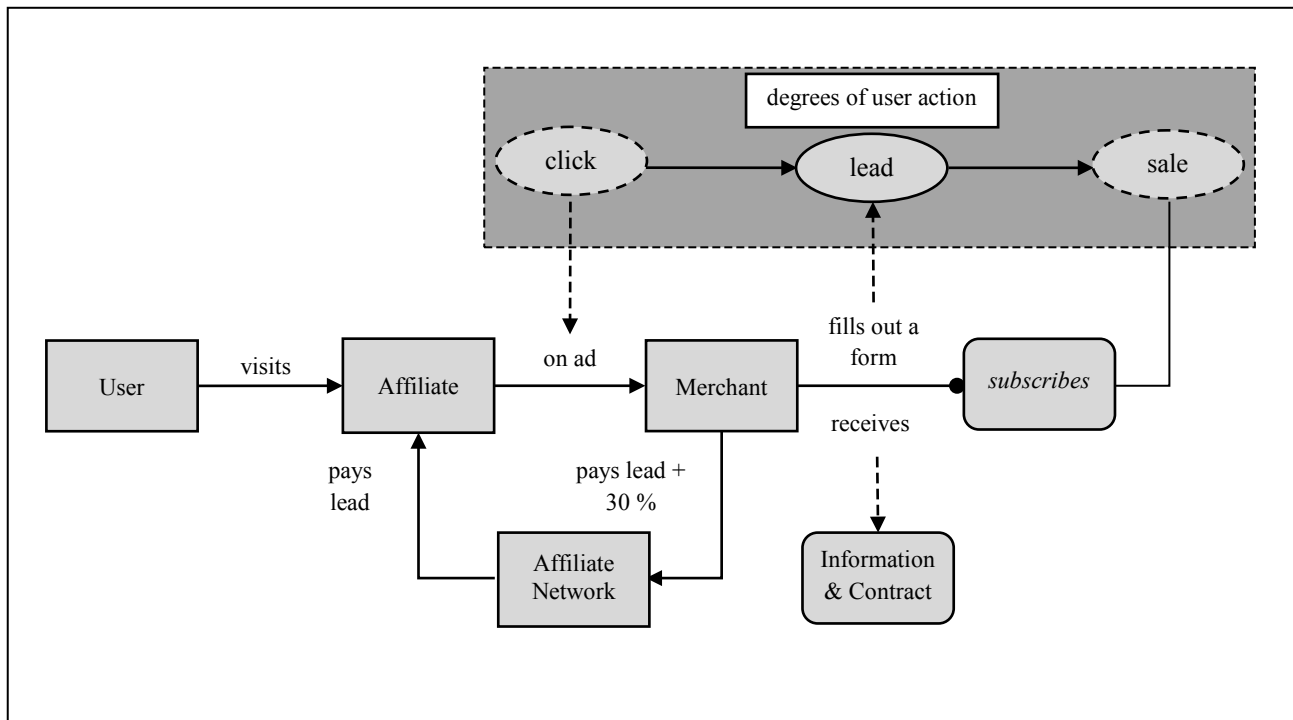
Figure 1:   Affiliate Marketing Process

Besides obvious benefits affiliate marketing can create challenges for mer-
chants, including the threat of fraud,[10] inaccurate brand behavior,[11] and the
search of appropriate affiliates with complementary products.[12] Thus, many
merchants evaluate affiliates according to key performance indicators (KPI)
and by their product focus, in an effort to ease the control and evaluation
process of their affiliate websites.[13] However, recent research calls for more
sophisticated approaches to the evaluating and controlling process of affili-
ates,[14] but still analyzes phrases from affiliate contracts like previous re-
searchers.[15] However, to control and evaluate affiliates and their perfor-
mance a merchant needs to know, how his affiliates act on their websites
and across other media channels and not how they should or would react
through contract designs.

*Fraud, inaccu-
rate brand be-
havior, search
for appropriate
affiliates*

*Factors of
controlling and
evaluating*

*Research
Question*

Thus our research question is**: What factors are relevant for a merchant
to control and evaluate its affiliates?**

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[10] C. f. EDELMAN/BRANDI 2014.

[11] C. f. FOX AND WAREHAM 2007; DANIELE ET AL. 2009.

[12] C. f. BANDYOPADHYAY/WOLFE/KINI 2009.

[13] C. f. OLBRICH/SCHULTZ/HOLSING 2015.

[14] C. f. GILLILAND/RUDD 2013.

[15] C. f. FOX AND WAREHAM 2010.

Instead of contract designs, we analyze real affiliate traffic from 329 affiliates of an education service merchant, across two European affiliate networks and over a five year period, to gain access to affiliates' actions and properties. Beyond that, merchants need insights into channel touchpoints by users.[16] In this manner, it learns and controls how well other advertising channels influence a user journey although they do not get the credit for. We address this issue, through a combination of the affiliate traffic data with data from the social networks Twitter and Facebook, and the perceived advertising channels by users during the affiliate marketing process (e.g. Google Search). We use a similar clustering approach as PAPATLA AND BHATNAGAR who focused on product closeness.[17] Instead, we focus on a high/low website focus of affiliates. For our study, we propose a two-step clustering approach combined with a Kruskal-Wallis-H test and a post-hoc analysis. The cluster analysis is an excellent exploratory data analysis tool in marketing research that identifies relevant website features for a control process.[18] Furthermore, this approach shows different types of affiliates, their rate of activity in the affiliate marketing process and their role across other user touchpoints. In this way, a merchant can easily identify his best performing affiliates, even if he already cancelled the relationship based upon false assumptions. To the best of our knowledge, no study so far used such a high volume data base and a similar exploratory approach. With this method, a merchant gains more control over and can better evaluate its affiliate portfolio in a very efficient and easy way.

Two European affiliate networks

Affiliate traffic data and social network data

Website focus clustering

Our paper is structured as follows: First, we give a brief literature overview in affiliate marketing and related instruments in advertising. Second, we show the structure of the data. Third, we give a descriptive overview and outline our method. After that we check for correlations among the data and choose further variables for the clustering process. After the clustering we validate the cluster solutions and discuss our results. Finally, we give implications for academics as well as practioners together with limitations of our study.

Structure of the research paper

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[16] C. f. LI/KANNAN 2014.
[17] C. f. PAPATLA/BHATNAGAR 2002.
[18] C. f. PUNJ/STEWART 1983; AYANSO/YOOGALINGAM 2009.

2. Literature Overview on Affiliate Marketing

2.1. Influences in the Relationship

Trust: In e-commerce settings, various drivers, including situational context, benevolence, privacy, or even an advisory function provided by the website influence the level of trust.[19] In affiliate marketing contexts, content providers enjoy the most trust and also need to maintain the most trust to ensure the success of their business model.[20] Several factors can enhance trust in affiliate marketing settings. For example, if an affiliate ranks in the top three search results on a search engine such as Google, users tend to perceive that affiliate as more trustworthy.[21]

Trust

Search Engines: Janssen and van Heck posit that the number of affiliates influences the natural ranking of a merchant.[22] The rank increases when it relies on more affiliates. This is not surprising as multi-channel influence is a common phenomenon[23] and affects offline/offline,[24] online/online,[25] and offline/online advertising[26] aspects altogether. For example Olbrich and Schultz found positive influences between Google ranks and magazines. That is, users search for brands, they recognized in a magazine before. Therefore, it seems reasonable that other advertising channels like social networks influence the affiliate marketing channel too.[27]

Search Engines

Channel influence

Perceived Usefulness: Affiliates that offer online coupons in their business model invoke higher perceptions of usefulness from users compared to perceived trust or informative eness.[28] Because coupons offer a high utilitarian benefit, they trigger better shopping experiences.[29] The search for and use

Usefulness

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[19] C. f. URBAN/SULTAN/QUALLS 2000; BART ET AL. 2005; LEE/TURBAN 2001; SCHULTZ 2006, 2007; URBAN/AMYX/LORENZON 2009.

[20] C. f. GREGORI/DANIELE 2011; GREGORI/DANIELE/ALTINAY 2014.

[21] C. f. GREGORI/DANIELE 2011.

[22] C. f. JANSSEN/VAN HECK 2007.

[23] C. f. ASSAEL 2011.

[24] C. f. HAVLENA/CARDARELLI/DE MONTIGNY 2007.

[25] C. f. NOTTORF 2014.

[26] C. f. NAIK/PETERS 2009; ZENETTI ET AL. 2014.

[27] C. f. OLBRICH/SCHULTZ 2014.

[28] C. f. UL HAQ 2012.

[29] C. f. CHANDON/WANSINK/LAURENT 2000.

of online coupons both depend on users' motivation, willingness to pay, and technical competency.[30] In this sense, perceived usefulness is not exclusive to affiliate marketing.

<div style="float:left">Social
Media Factors</div>

Social Media: According to MARIUSSEN, BOWIE, and PARASKEVAS, social media activities by affiliates are interesting external factors in affiliate marketing.[31] But, the research stream in social media not focuses on affiliate marketing. Instead, research investigates mostly users, such as their brand recommendations through social networks or their use of Twitter for self-enhancement.[32] Other studies also consider how marketers might use social networks, such as by identifying social clickers on blogs and using them to drive word-of-mouth campaigns.[33] Thus, social networks require modifications to existing communication models,[34] to account for what Yadav ET AL. label the computer-mediated social environment.[35] So, we consider the consequences when the user of a social network is an affiliate, in which case a computer-mediated social environment should increase competition. Because an affiliate normally participates in several relationships, its greater social activity might indicate a broader target audience but also increased competition for any single merchant.

<div style="float:left">Social
Environment</div>

2.2. Principal-Agent Relationship

<div style="float:left">Moral Hazard
and Adverse
Selection</div>

Moral Hazard and Adverse Selection: During the relationship between a principal and his agents, the principal delegates specific tasks to its agents that it cannot completely observe.[36] Consecutive, some might say that the relationship between merchants and affiliates is generally a principal-agent relationship, because the merchant cannot observe every action of his affiliates. In turn, the principal, respectively the merchant depends heavily on the agent's (affiliate's) selling skills.[37] But, if the merchant chooses affiliates

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[30] C. f. CHANDON/WANSINK/LAURENT 2000; SURI/SWAMINATHAN/MONROE 2004; SHOR/OLIVER 2006.
[31] C. f. MARIUSSEN/BOWIE/PARASKEVAS 2012.
[32] C. f. CHATTERJEE 2011; BERGER/IYENGAR 2013.
[33] C. f. GREG 2004; RIEGNER 2007; KOZINETS ET AL. 2010; HOLSING/SCHULTZ 2013.
[34] C. f. HOFFMAN/NOVAK 1996.
[35] C. f. YADAV ET AL. 2013.
[36] C. f. JENSEN/MECKLING 1976.
[37] C. f. BASU ET AL. 1985

poorly or without regard to their skills, it risks adverse selection.[38] Especially, when an affiliate wants to trick the merchant, it might seek to become one of many agents, which enables it to hide and act as an impostor – a threat that Libai, Biyalogorsky and Gerstner refer to as the free-rider problem.[39] Free-riding is therefore similar to moral hazard,[40] in the sense that the merchant cannot observe the action of every affiliate or detect every instance of fraud or brand inconsistency.[41]

Monitoring Moral Hazard: Fox and Wareham examine the governance mechanisms used by 136 affiliate programs,[42] considering both outcome- and behavior-based control systems[43] as monitoring possibilities for a merchant working in ‚electronic channels'[44]. On the basis of their findings, they advise regular checks on KPIs to observe the outcome achieved by the affiliates, as well as careful behavioral monitoring by regularly checking the affiliates' websites and search engines. Yet Gilliland and Rudd also caution that cheating behavior increases with the dynamism of the industry, because when dynamism and competition are high, as is the case for web channels, affiliates prefer short relationships.[45] Therefore, these authors suggest that merchants should develop and monitor in-house affiliates, to gain more control over their contracts, KPIs, and other management tools.

2.3. Relationship Determinants

Product Categories: Papatla and Bhatnagar distinguish affiliates according to whether they offer temporal or substitutable consumer goods and argue that episodic complements (e.g., wine and flowers) can increase utility.[46] This implies that the consumption of one product is possible without the other, but together, they offer greater benefits for the user. A merchant specializing in flowers therefore should cooperate with an affiliate website that specializes in wine, and vice versa. Such findings suggest limitations on the

Free-rider problem

Monitoring Moral Hazard

Episodic complements

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[38] C. f. EISENHARDT 1989.
[39] C. f. LIBAI/BIYALOGORSKY/GERSTNER 2003.
[40] C. f. HOLMSTRÖM 1979.
[41] C. f. MARIUSSEN/BOWIE/PARASKEVAS 2010.
[42] C. f. FOX/WAREHAM 2010.
[43] C. f. ANDERSON/OLIVER 1987.
[44] C. f. CELLY/FRAZIER 1996.
[45] C. f. GILLILAND/RUDD 2013.
[46] C. f. PAPATLA/BHATNAGAR 2002.

potential partners for merchants. Therefore a relationship between a wine merchant and an affiliate that offers books seems not meaningful, even if a book about wine would be an obvious link.

<div style="float:left; width:25%; text-align:right; font-style:italic;">
Success depends on product, user, and affiliate characteristics
</div>

Product Complexity and Involvement: Users spend more time on affiliate websites when they are searching for homogenous, highly comparable products, whereas complex products (e.g., insurances) lower the user's acceptance for more information.[47] Thus the success of affiliate marketing depends on product characteristics, as well as user or affiliate characteristics. To model user characteristics like the involvement[48] in affiliate marketing, it is possible to link higher levels of user involvement with different user actions.[49] For example, a sale indicates greater interest and involvement than a mere click or a lead in an affiliate marketing setting.[50]

<div style="float:left; width:25%; text-align:right; font-style:italic;">
Super affiliates are unique
</div>

Types of Affiliates: Highly valuable affiliates generate the most traffic and revenue. There are only a few of these unique, "super affiliates" in any merchant's portfolio.[51] In contrast, emerging and hobby sites tend to be the most common affiliates for a merchant.[52] Despite their vast numbers, they generate only a moderate amount of traffic.[53] Other notable affiliate types include specialized, bogus, and poor fit websites.

2.4. Short Comparison with Classic Banner Advertising

We offer a short summary of classic banner advertising literature, to highlight its similarities and differences from affiliate marketing. Because affiliate websites use digital advertisements they underlie the same issues like classic banner advertising. Some of these are potentially cannibalizing effects on clicks through multiple ad links to a website[54] or the impact of banner animation on clicks.[55] That includes the research of psychological constructs such as brand loyalty, awareness, or recognition too.[56] However,

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[47] C. f. BREAR/BARNES 2008.
[48] C. f. KRUGMAN 1965; LASTOVICKA 1979; LASTOVICKA/GARDNER 1978.
[49] C. f. OLBRICH/SCHULTZ/HOLSING 2015.
[50] C. f. GOLDSCHMIDT/JUNGHAGEN/HARRIS 2003.
[51] C. f. BROWN 2009.
[52] C. f. FIORE/COLLINS 2001.
[53] C. f. GOLDSCHMIDT/JUNGHAGEN/HARRIS 2003; GREGORI/DANIELE/ALTINAY 2014.
[54] C. f. HOFACKER/MURPHY 2000.
[55] C. f. CHANDON/CHTOUROU/FORTIN 2003; LEE/AHN 2012.
[56] C. f. BRIGGS/HOLLIS 1997; CHO 2003; DRÈZE/HUSSHERR 2003.

performance measures for classic banner advertising often use a view or click to measure users' interest.[57] Therefore, companies pay a commission to partners for every tracked click or impression,[58] whereas in affiliate marketing additional transactions are measured. Thus, classic banner advertising stops with the click, whereas measures for affiliate marketing persist and track additional user actions.

Affiliate marketing tracks more user actions

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[57] C. f. BRAUN/MOE 2013; OLBRICH/SCHULTZ/HOLSING 2015.
[58] C. f. HOFFMAN/NOVAK 2000.

3.   Data Analysis and Clustering Approach

3.1. Structure of the Data

We use data of an affiliate marketing campaign by a private education merchant which includes 329 affiliates. The dataset contains 179,338 unique clicks by users who visited the merchant's website. 5,340 Leads were generated. That means 5,340 users ordered further education information about the merchant's service. 82 users finally signed up for the service of the merchant, and triggered a sale. Each sale brings the merchant a marginal income of 3.000 €. Every affiliate is paid on a 5 € pay-per-lead basis. Thus, the merchant paid nearly 25,000 € for this affiliate marketing campaign. Although, the merchant is sure that this data includes bogus affiliates and therefore bogus LEADS, it has not yet completely identified, we keep it for the sake of real data. We do not question the population of affiliates as we try to identify all types of affiliates. Third-party-agencies and two leading affiliate networks automatically track the data for the merchant. The affiliate networks are belboon and affilinet, the latter of which focuses only on Europe.[59] The merchant collected data from July 1, 2009, to July 31, 2013; we complemented these data with Twitter and Facebook activities of the merchant's affiliates during March 1–July 31, 2013. As a private education provider, the merchant offers different courses, for which a user pays. If the user finishes the course, the merchant certifies her or his graduation. A user without any basis in economics might need 15 months to complete a management course, whereas one with prior economics knowledge might need only 6–8 months. The user is responsible for determining his or her existing knowledge and willingness to accept risk, because the date of completion, test results, and career impact of the earned grade remain unknown and are not guaranteed by the non-university, private education service. Functional services normally induce a high involvement, a raise in comparing and searching information,[60] and a higher risk.[61] So, users consider multiple channels to evaluate available services, including experiences described by

329 Affiliates with 5,340 users

82 Sales

5 € pay-per-lead

Data from Belboon and Affilinet

Data from Twitter and Facebook

Functional services induce a high involvement

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[59] C. f. PRUSSAKOV 2007.

[60] C. f. MITTAL 1989.

[61] C.f. LAURENT/KAPFERER 1985.

other users in social networks[62] or alternatives available through third-party sites, before making a purchase decision.[63]

Perceived
Channel
touchpoints

In addition to the automatic tracking, the analyzed merchant offers users the chance to quote their first advertising channel that drove their attention to the merchants' website (e.g., newspaper). However, no option in the menu names "affiliate" as the responsible advertising channel, although every user in our dataset has its origin from an affiliate website. We suggest, the merchant assumes that users are not familiar with the affiliate marketing concept. Therefore, it is likely it uses the "communities" choice to measure the impact of affiliates, because communities are a common form of affiliates.[64]

3.2. Two-Step Clustering Approach and Kruskall-Wallis-H Test

Dividing
variables into
two participants

Figure 2 shows our final variables. We class these variables into two participants in the affiliate marketing process: affiliates of the merchant and users who click an ad and complete a form on the merchant's website. First, we classify BANNER/TEXT ADS PER DAY, WEBSITE FOCUS, and PARTNERSHIP as affiliates' properties and actions. Second, we classify the variables related to social media channels to the affiliates' Social Factors. Third, we distinguish AD VIEWS PER DAY from CLICK, LEAD, and SALE measures, because the affiliate controls the AD VIEWS PER DAY with the amount of impressions by itself.

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[62] C. f. YADAV ET AL. 2013.

[63] C. f. MAGNINI/KARANDE 2011.

[64] C. f. HELMSTETTER/METIVIER 2000.

Variable	Description
PARTNERSHIP	Active affiliate on July, 31 2013
WEBSITE FOCUS	Education or non-education focus
AD VIEWS PER DAY	Impressions the affiliate used in a 24-hour day
TEXT ADS PER DAY	Text ads the affiliate used per day
BANNER ADS PER DAY	Banner ads the affiliate used per day
TWEETS	Tweets on the affiliate's Twitter profile
FOLLOWING	Profiles the affiliate follows
FOLLOWER	People following the affiliate's profile on Twitter
LIKES	Likes on the affiliate's Facebook profile
PEOPLE TALKING	People talking about the content on the affiliate's
ABOUT THIS	Facebook profile
CLICKS PER DAY	Ad clicks by users per day
LEADS	Requested information by users
SALES	Subscribed contracts
GOOGLE SEARCH	Users who indicate they were attracted by a Google search
GOOGLE ADS	Users who indicate they were attracted by a paid Google ad
BANNER OR TEXT AD	Users who indicate they were attracted by a display ad
NEWSPAPER AD	Users who indicate they were attracted by a newspaper ad
COMMUNITIES	Users who indicate they were attracted by a community
ACQUAINTANCES	Users who indicate they were attracted by a recommendation
FACEBOOK	Users who indicate they were attracted by a Facebook profile

Figure 2:   Variables used in Study

Further, we refer to the KPIs CLICK, LEAD, and SALE as a user action chain with different levels of activity. That means we focus on degrees rather than single actions of interest. Because the perceived advertising channel reflects the user's choice from a drop-down menu, both degrees of user action and perceived advertising channel variables are user-specific feedback.

KPIs are Click, Lead and Sale

Subsequently, we apply a two-step cluster analysis to group affiliates and identify the behavior of the affiliates actions and properties on its website and across social media channels. Additionally, we observe the cross channel activities by other online advertising channels. The two-step clustering method is a reasonable exploratory approach for aggregating properties and behavior of different e-commerce groups, e.g. web-retailers,[65] and achieve a better control process. With a two-step cluster analysis, we can deal with the continuous, categorical nature of the variables, because this method allows for mixed measurement levels. Furthermore, we adopt a random allocation of records within the dataset, to prevent clustering of similar records.

Two-Step Clustering is a reasonable exploratory approach

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[65] C. f. AYANSO/YOOGALINGAM 2009.

Preventing
Auto-
Clustering

Information
criteria and
outlier check

Accordingly, we added three variables to the dataset, with random numbers from 1 to 329, and sorted the results on the basis of these variables every time we conducted the analysis, checking for any outliers at the 1% level. Normally, a Two-step cluster analysis offers two information criteria, Bayesian and Akaike's. But, the former criterion often underestimates cluster solutions, whereas the latter overestimates them.[66] Thus, we use a specific cluster philosophy[67] and therefore choose five clusters. We anticipate that the dataset should include five clusters because the PARTNERSHIP and the WEBSITE FOCUS are dual coded and therefore indicate the highest distance.

Non-Normality
and Correlation

These clusters mirror average affiliates (e.g. hobby affiliates), cancelled affiliates (because of poor performance), and 'super affiliates' with a high or low education focus. With this approach we address our explorative research,[68] and therefore help managers to apply our strategy in an efficient way. With the Pearson correlation, we identified variables with a maximal correlation of .2 to inform our clustering process, which represents a low level of correlation[69] and prevents similarity-based clustering of highly correlated variables. Nonetheless, the two-step clustering can deal with this violation also.[70] Finally, we examine the distribution of the degrees of user actions in our cluster solution, using a Kruskal-Wallis-H test and a post-hoc analysis with sum of ranks, because our data set is not normally distributed. Multiple pairwise comparisons reveal which clusters are responsible for any differences.

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[66] C. f. KUHA 2004.

[67] C. f. BURNHAM/ANDERSON 2004.

[68] C. f. MOOI/SARSTEDT 2011.

[69] C. f. COHEN 1992.

[70] C. f. CHIU ET AL. 2001; IBM 2011.

3.3. Descriptive Results

Figure 3 shows the descriptive statistics of our data. According to the distribution of partnerships, nearly half of the affiliates are no longer active, and

Type of Variable			Variable	Mean	SD	Max
AFFILIATES	ACTIONS AND PROPERTIES		PARTNERSHIP	.49 [161/168][a]	.50	1
			WEBSITE FOCUS	.61 [199/130][a]	.49	1
			AD VIEWS PER DAY	47.15	306.84	4,692.83
			TEXT ADS PER DAY	.74	1.37	20
			BANNER ADS PER DAY	.92	.64	4
	SOCIAL FACTORS		TWEETS	278.21	1,536.1	15,879
			FOLLOWING	108.25	1,297.3	23,135.50
			FOLLOWER	136.41	1,252.2	21,954.22
			LIKES	94.51	842.43	13,577.40
			PEOPLE TALKING ABOUT THIS	5.02	74.08	1,339.30
USERS	DEGREES OF USER-ACTION (KPIS)		CLICKS PER DAY	1.30	6.77	113.71
			LEADS	16.23	77.14	1,013
			SALES	.25	1.50	21
	PERCEIVED ADVERTISING CHANNEL		GOOGLE SEARCH	4.68	26.48	343
			BANNER OR TEXT AD	1.75	9.86	121
			NEWSPAPER AD	1.31	18.76	339
			COMMUNITIES	1.04	4.68	41
			ACQUAINTANCES	.75	4.31	46
			GOOGLE ADS	1.94	10.60	140
			FACEBOOK	.03	.19	2

Figure 3:   Descriptive Statistics[71]

we find a small imbalance in favor of education-related affiliates. Thus, the merchant focuses mainly on affiliates that match its own business. In addition, affiliates appear to run one distinct ad per day. Standard deviations and maximum values imply that if they use another ad, it likely is a textual one. Activity occurs in both social networks, and reaches for example a maximum of 21,954 followers. The transaction data also show at least one click on each affiliate's ad per day, representing chances for the merchant to con-

Affiliates use text ads more often

One click per day

[71] There are 329 affiliates in our dataset. The minimum value is always 0. For views and used ads, if affiliates failed to integrate a tracking pixel in the source code, the value is 0. A click counts as the least involved transaction. [a]The first value in rectangular brackets shows the frequency of active and education-related affiliates.

vince a user to purchase its service. GOOGLE-SEARCH (M_{Google}=4.68, Max_{Google}=343) and NEWSPAPER ADS ($MAX_{NewspaperAd}$=339) are the most dominant forms of perceived advertising channels in the data set. This indicates, that search engines and newspaper ads have a positive effect on later user transactions redirected by affiliates. These findings are in line with previous academic results regarding online and offline advertising campaigns.

Figure 4 contains the correlations within the data set. FOLLOWER and FOLLOWING correlate strongly, though if a user follows another user on Twitter, it often initiates a re-following process.[72] Thus, this correlation indicates a user-appreciated norm. For the clustering, we may include only one of these variables. We chose FOLLOWERS, because social network
users tend to join groups that share similar interests, producing social homophily.[73] Therefore, followers of an affiliate's Twitter or Facebook profile likely are interested in the affiliate's main topic, such as education. Accordingly FOLLOWERS represent potential customers of the merchant. The variables LIKES and PEOPLE TALKING ABOUT THIS also are highly correlated; because PEOPLE TALKING ABOUT THIS offers more textual information,[74] we prefer to use it in the clustering process. With regard to degrees of user action, LEADS and SALES correlate with each other but not with CLICKS. It seems inappropriate to differentiate the phases within the chain of actions, so we chose not to separate CLICKS from LEADS and SALES but instead used these variables as descriptions of the formed cluster solutions. Perceived advertising channels create a similar situation. For example, we find high correlations between KPIs and the advertising channels, such that SALES correlate highly with GOOGLE SEARCH, and COMMUNITIES correlates with ACQUIANTANCES. Therefore, we employed the different advertising channels as descriptive variables.

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[72] C. f. STIEGLITZ/DANG-XUAN 2013.

[73] C. f. ARAL/MUCHNIK/SUNDARARAJAN 2009.

[74] C. f. INSIDEFACEBOOK 2012.

	Affiliates' Actions and Properties					Affiliates' Social Factors					Degrees of User Action					Perceived Advertising Channels				
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 Partnership	1																			
2 Website focus	.169**	1																		
3 Ad views per day	-.045	-.070	1																	
4 Text ads per day	.137**	.008	-.035	1																
5 Banner ads per day	-.050	.059	.158**	-.144**	1															
6 Tweets	.055	-.073	.002	-.040	-.026	1														
7 Following	.051	.018	-.012	-.036	.007	.290**	1													
8 Follower	.072	.032	-.015	-.022	-.002	.321**	.981**	1												
9 Likes	.008	-.088	-.015	.040	-.081	.098*	.010	.091*	1											
10 People talking about this	-.044	-.075	-.009	.019	-.085	.050	.001	.075	.905**	1										
11 Clicks per day	-.050	-.033	.117*	-.011	.038	-.026	-.007	-.007	-.013	-.011	1									
12 Leads	.123*	.020	.083	.110*	.248**	-.026	-.016	-.008	-.016	-.014	.114*	1								
13 Sales	.166**	.031	.011	.122*	.096*	-.018	-.013	-.002	-.006	-.010	.098	.813**	1							
14 Google search	.169**	.038	.021	.111*	.119*	-.020	-.013	-.001	-.011	-.011	.110*	.898**	.861**	1						
15 Banner or text ad	.065	.087	.023	-.030	.212**	-.030	-.014	-.016	-.019	-.012	.032	.342**	.055	.097	1					
16 Newspaper ad	-.042	-.069	.159**	.057	.294**	-.012	-.006	-.007	-.008	-.005	.030	.477**	.074	.130**	.262**	1				
17 Communities	.151**	.109*	.005	.046	.161**	-.031	-.017	-.006	-.020	-.015	.071	.718**	.515**	.669**	.709**	.153**	1			
18 Acquaintances	.132**	.019	.074	.079	.274**	-.021	-.013	.000	-.012	-.011	.090	.861**	.666**	.782**	.328**	.385**	.618**	1		
19 Google ads	.167**	.041	.031	.111*	.138**	-.014	-.014	-.001	-.010	-.011	.110*	.900**	.870**	.983**	.114*	.154**	.657**	.785**	1	
20 Facebook	.132**	.031	-.010	.068	.093*	.009	-.012	-.003	.008	-.009	.041	.401**	.371**	.435**	.117**	.032	.330**	.482**	.409**	1

Figure 4:   Correlations among the Variables[75]

75 Because the correlation between text and banner ads is less than .2 and thus weak, we use them for the clustering process.
**Significant at .05. *Significant at .01.

3.4.   Results of the Cluster Analysis

Website focus,
partnership and
social factors
determine the
cluster
solutions

In Figure 5 we provide the final clustering result. The scale for overall model fit spans from -1.0 to 1.0, where a negative value indicates a bad fit; the fit for our model is .8. Thus, we find a good fit for our clustering results. The clusters reveal the following affiliate types: average affiliates, cancelled affiliates and super affiliates. The clusters also reveal the following ranking: SOCIAL FACTORS take the third (0.51), fifth (0.13), and sixth

		Cancelled Affiliates 87	Average Affiliates 108	Super Affiliates 12	Cancelled Affiliates 74	Average Affiliates 48
Clustering variables	Website focus (1.0)	Education	Education	Mixed (67% non-education)	Non-education	Non-education
	Partnership (1.0)	No	Yes	Mixed (58% no)	No	Yes
	Tweets (0.51)	.14 [1.35]	126.42 [126.42]	5,257.62 [5,905.92]	71.78 [314.99]	197.10 [810.14]
	Ad views per day (0.28)	16.80 [42.39]	17.86 [60.15]	830.38 [1,409.59]	15.92 [99.88]	20.36 [49.46]
	Follower (0.13)	1.90 [17.69]	93.18 [384.86]	2,492.33 [6,208.14]	25.44 [179.59]	59.57 [235.79]
	People talking about this (PTAT) (0.07)	0.02 [0.14]	0.70 [4.32]	114.25 [385.86]	0.52 [4.49]	3.42 [14.49]
	Text ads per day (0.06)	0.47 [0.69]	1.00 [1.04]	2.11 [5.68]	0.41 [0.53]	0.85 [0.95]
	Banner ads per day (0.01)	1.02 [0.52]	0.90 [0.70]	1.12 [1.15]	0.83 [0.58]	0.86 [0.64]
Descriptive variables [non-clustering]	Clicks per day	0.80	1.03	4.17	2.12	0.84
	Leads	5.45	27.77	50.00	1.49	24.10
	Sales	0.01	0.52	0.00	0.00	0.52
	Google search	0.25	9.90	2.42	0.11	8.56
	Banner or text ad	1.34	3.41	4.00	0.32	0.35
	Newspaper ad	0.03	0.47	28.25	0.11	0.65
	Communities	0.53	2.24	0.75	0.04	0.85
	Acquaintances	0.05	1.46	2.42	0.04	1.08
	Google ads	0.16	4.05	1.83	0.08	3.31
	Facebook	0.01	0.06	0.00	0.00	0.06

Figure 5:   Clustering Results[76]

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[76] We sorted the variables by their importance, from 1.00 to 0.00. The standard deviations are in square box brackets. A missing percent indicates a full 100 %.

position (0.07), right after WEBSITE FOCUS (1.0) and PARTNERSHIP (1.0). Despite the importance of AD VIEWS PER DAY (0.28), we find no deeper relevance associated with using different ad types.

The lower the focus, the higher the social activity

The clustering variables in figure 5 highlight the variables we used for the clustering process. *Clustering Variables:* The cluster means show a wide spread in the SOCIAL FACTORS for active affiliates. Especially active affiliates with a non-education-related WEBSITE FOCUS have a higher social activity in Tweets and PTAT ($M_{non-education/active/Tweets}$=197.10, $M_{non-education/active/PTAT}$=3.42) than education-related affiliates ($M_{education/active/Tweets}$=126.42, $M_{education/active/PTAT}$=0.70). Looking at the FOLLOWERS, education-related Affiliates outperform non-education-related Affiliates ($M_{education/active/Follower}$=93.18, $M_{non-education/active/Follower}$=59.57). The coordination between AD VIEWS A DAY and AD TYPE variables seem nearly equivalent for all affiliates, regardless if the affiliate partnership were cancelled. The variables for the super affiliates display a clearly different structure compared with the other affiliate types, such that these affiliates concentrate on attracting many AD VIEWS, use a lot of different AD TYPES, and are extremely active in social networks. As the PARTNERSHIP variable illustrates, not all affiliates remain active in this cluster. In fact, 67 % (7) of the Super Affiliates have a non-education-related WEBSITE FOCUS. In contrast with the definition of a super affiliate, these super affiliates generate no SALES. We address this issue later in the discussion section.

The higher the focus, the higher the potential of new customers

Super Affiliates have no Sales

The descriptive variables in figure 5 highlight the variables we not used for the clustering process but to describe the final clusters more appropriate. *Degrees of User-Action:* Cancelled affiliates with a non-education WEBSITE FOCUS and super affiliates have more user CLICKS than other affiliate types ($M_{non-education/non-active}$=2.12, $M_{super\ affiliates}$=4.17). Yet, means of CLICKS show that average affiliates and cancelled affiliates have the same CLICKS on a day (for example: $M_{education/cancelled}$=0.80, $M_{non-education/active}$=0.84). As expected, cancelled affiliates generate less LEADS ($M_{non-education/cancelled}$= 1.49, $M_{education/cancelled}$=5.45), than average affiliates ($M_{education/active}$=27.77, $M_{non-education/active}$=24.10), and super affiliates show the most LEADS ($M_{super\ affiliates}$=50.00). Both types of average affiliates generate the same SALES ($M_{non-education/active}$=0.52, $M_{education/active}$=0.52). However, non-education-related affiliates generate the same amount of SALES with fewer LEADS ($M_{non-education/active}$=24.10) and affiliates (48) than their educa-

Super affiliates have the most clicks and leads

Cancelled affiliates have less leads

tion-related counterparts ($M_{education/active}$=27.77, 108). Furthermore, a few affiliates with an education-related WEBSITE FOCUS were cancelled, although they generated SALES ($M_{education/non-active}$=0.01).We address this issue at our discussion section.

Perceived Advertising Channels: The values for GOOGLE SEARCH and GOOGLE ADS in average clusters ($M_{education/Google-Search}$=9.90, $M_{education/Google-Ads}$=4.05, $M_{non-education/Google-Search}$=8.56, $M_{non-education/Google-Ads}$=3.31) are the dominant perceived advertising channels for all users. These values are far greater than the scores for COMMUNITIES ($M_{education/Communities}$=2.24, $M_{non-education/Communities}$=0.85), which we used to measure the advertising channel ‚Affiliate'. Super affiliates have the highest perception of NEWSPAPER ADS ($M_{super\ affiliates}$=28.25), ACQUAINTANCES ($M_{super\ affiliates}$=2.42) and BANNER OR TEXT ADS ($M_{super\ affiliates}$=4.00). Despite their high activity in Facebook, no user perceived this advertising channel ($M_{super\ affiliates}$=0.00) when redirected by these affiliates. Cancelled affiliates have the lowest perception values of all advertising channels, except for BANNER OR TEXT AD ($M_{education/non-active/Banner\ or\ Text\ Ad}$=1.34, $M_{non-education/active/Banner\ or\ Text\ Ad}$=0.35). This is not surprising, because users can only name an advertising channel, when the affiliate redirects them to the merchant website. With less leads come less perceived advertising channels.

3.5. Results of the Kruskall-Wallis-H and Post-hoc analysis

With a Kruskal-Wallis-H test, we compare the five clusters on the basis of the sum of their ranks of CLICKS, LEADS, and SALES, using the clusters as group samples. The post-hoc analysis bases on a multiple pairwise comparisons which rely on a Dunn-Bonferroni correction.[77] Therefore, our analysis includes all the data, instead of data for just two groups, and we can test our proposition that our clustering variables are responsible for the distribution of the degrees of user action. We apply this method in order to determinate whether means of differences among the clusters observed are not accidental. We expect variance in the rankings for CLICKS and LEADS in our cluster solution. Affiliates worry about CLICKS, even if they are not paid for them, so an affiliate might alter the type of

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[77] C. f. DUNN 1964; IBM 2012.

(margin notes)
Google-Search and Google-Ads dominate average clusters

Communities are far more visible for an education focus

Newspaper Ads and acquaintances are mainly perceived for super affiliates

the ad (BANNER/TEXT) to increase awareness and likelihood of a CLICK. They also are very interested in commissions,[78] which are paid on a per lead basis, so they use social networks to expand their reach and gather more LEADS and thus commissions. A CLICK can induce the conditional action of a LEAD (i.e., a LEAD cannot exist without a previously generated CLICK). Finally, a SALE should be outside the affiliates' focal interest, because it does not get paid more for additional sales. In turn, we issue two alternative hypotheses:

H_0: The distributions of (a) CLICKS and (b) LEADS are equal across all clusters, and (c) the distribution of SALES varies between at least two clusters.

H_1: The distributions of (a) CLICKS and (b) LEADS vary between at least two clusters, and (c) the distribution of SALES is equal among all clusters.

The results reveal a statistically significant distribution of CLICKS between the cluster solutions ($\chi^2(4) = 16.010$, $p = .03$), so we reject H_{0a} and confirm that CLICKS vary between at least two clusters. We also reject H_{0b} ($\chi^2(4) = 32.322$, $p = .00$), because the distribution of LEADS varies between at least two clusters too. However, we cannot reject H_{0c} ($\chi^2(4) = 29.584$, $p = .00$). Thus, the distribution of SALES varies also. Finally, we conducted a post-hoc analysis to analyze which clusters prompted the differences in the sum of ranks, as we detail in figure 6.

H_{0a-b} reject Clicks and Leads vary between all clusters

H_{0c} not reject Sales **not** vary between cluster solutions

Affiliate Type	T1	T2	T3	T4	T5		
Degrees of User Action	Cancelled Affiliates (Education)	Average Affiliates (Education)	Super Affiliates	Cancelled Affiliates (Non-education)	Average Affiliates (Non-education)	Adjusted Sig. (two-tailed .05)	Relevant Cluster Comparisons
Clicks per day	140.37	192.12	183.00	155.40	158.91	**.002****	**T1-T2**
Leads	169.94	192.98	171.42	121.13	159.12	**.003**** **.000****	**T1-T4** **T2-T4**
Sales	155.33	182.41	153.50	153.50	163.97	**.000**** **.000****	**T1-T2** **T2-T4**

Figure 6:   Sum of Ranks and adjusted Significance for Cluster Solutions

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[78] C. f. AFFSTAT REPORT 2013.

Super affiliates are not responsible for the differences in the KPIs

A significant gap arises in CLICKS and SALES ($SUM_{Clicks/T1}$=140.37, $SUM_{Clicks/T2}$=192.12, $SUM_{Sales/T1}$=155.33 $SUM_{Sales/T2}$=182.41) between T1 and T2. Furthermore, we find significant gaps in LEADS between T1 and T4 ($SUM_{Leads/T1}$=169.94, $SUM_{Leads/T4}$=121.13) and T2 and T4 ($SUM_{Leads/T2}$=192.98 $SUM_{Leads/T4}$=121.13). These differences show the performance between education-related affiliates in general and cancelled non-education related affiliates. The last gap arises in SALES between T2 and T4 ($SUM_{Sales/T2}$=182.41 $SUM_{Sales/T4}$=143.50). This difference in sum of ranks address average education related affiliates and cancelled affiliates with non-education websites. However, the super affiliates are not responsible for the differences. We discuss this cluster comparisons in our next section.

4. Discussion

In this study, we conducted a two-step cluster analysis with a Kruskal-Wallis-H Test, and a post-hoc analysis to show affiliates' behavior on their websites and across other advertising channels like social media channels. Additionally, we identified five different types of affiliates and showed that the super affiliates not behaved like expected, suggesting there are no super affiliates. This exploratory approach helps to uncover control variables for merchants away from contract design research.

Clustering Variables

Actions and Properties: The results of our clustering suggests that the ad performance of the affiliates is nearly the same for ad-views a day and for different ad-types a day. Only means of super affiliates show an exaggerated use of different ad types. Thus, a raise in LEADS seems limited and affiliates not achieve it with a higher use of different ad types. Yet, if an affiliate already uses one ad, it is likely that text ads are a favorite choice for a better lead controlling.

Ad-Performance is equal across clusters

Social Factors: The ranking of our clustering variables suggests that social behavior is an important control variable to merchants when they seek new affiliates. Every cluster exhibit at least a certain activity in both social networks. Cancelled affiliates had the lowest power in social behavior. Therefore, it appears that merchants should try to use affiliates with social networks as a supplement to their website. In return, an affiliate raises its chances to be in the main salesforce of a merchant.

Social Factors are not equal across clusters

Social Factors are an essential supplement for affiliates

Descriptive Variables

Clicks: Although affiliates are not paid for clicks, affiliate websites with a focus close to the merchant's branch have the highest sum of ranks (distance) in clicks, although super affiliates had the most clicks. Therefore, it seems a click is more valuable in this cluster than in all other clusters. Merchants that not pay for clicks should seek affiliates with a website focus close their own products or services if they want to raise and control clicks.

Education-related Affiliates cause the highest distances in clicks

Leads: Because the examined merchant uses a pay-per-lead assessment, a high distance in LEADS does not necessarily constitute the best distance between cluster solutions. Affiliates with an education-related website, whether active or not, achieve a better LEAD performance in sum of ranks than non-education related affiliates (T1-T4, T2-T4). But as long as the merchant pays for LEADS, he needs effective LEADS that turn into sales (*conversion rate*). Therefore, a low distance indicates a better lead perfor-mance in relation to sales. Merchants that rely on LEADS, gain more effec-tive LEADS with affiliate websites that are not close to the merchants' products or services because this indicates a lower competition.

Sales: Although cluster T2 is responsible for the most distances, affiliates in cluster T5 have a better performance. They are less in numbers and have a lower distance in LEADS, but generate the same sales as affiliates in T2. Therefore, the merchant pays less for them, but generates the same revenue. The overall amount of sales indicate that it may be possible that a single SALE has more importance in the education sector than in other sectors (e.g. books). We assert that the rate of sales may be less important than the amount, and a small change in SALES for affiliates could explain a signifi-cant difference. However, the merchant cancelled affiliates in T1 although they generated sales.

Perceived Advertising Channels: Before we discuss our results in detail, recall that all transactions were initiated through the affiliates, regardless of the users' choices from the drop-down menu. Our clustering results reveal that a search engine is dominantly perceived in the user journey. Only affil-iates with a WEBSITE FOCUS close to the merchant's business branch show a greater perception of communities. Thus, some affiliates might per-suade users on their own. Further, super affiliates build a melting pot for users recognizing the merchant's brand in a newspaper ad. These affiliates also show the highest score in acquaintances, suggesting that users seek out their friends' recommendation to begin with the search for further educa-tion. To raise the power of its affiliates, a merchant should use additional advertising channels that increase visibility of the brand for example search engines or newspaper ads.

Types of Affiliates

Our study revealed that the super affiliates not behaved like expected. The post-hoc analysis showed that besides its high metrics in CLICKS and LEADS, the super affiliates are not responsible for the differences in our cluster solution. Furthermore, these affiliates generated no SALES as the cluster analysis revealed. It appears that this cluster contains affiliates that work with many competitive merchants, because their vast social activity attracts many potential customers and multiple merchants. Yet, this explanation cannot account for the absence of SALES, which further indicates that a) the merchant's offer fails to convince users or b) these clusters show the power of bogus leads by fraudulent affiliates. Although it is possible that affiliates in our 'super affiliate' cluster use a social network to cover unsolicited behavior, we believe their digital trace[79] would uncover this behavior at an early stage. On the basis of this reasoning, we assert it is more likely that the offer could not persuade the user. Otherwise, the merchant had the chance to address more users than usual, even if its offer lacks attraction. Therefore, the greater competition may represent a trade-off for increased leads. Thus, merchants and affiliates may use social networks to form a structurally advantageous position against other merchants or affiliates. If the merchants offer isn't convincing by itself, a super affiliate is barely useful without the appropriate help of the super affiliate. In conclusion, merchants should not solely rely on KPIs for super affiliate measurement. However, if there are any affiliates with exaggerated performance in social networks, the merchant should contact these affiliates. Either to elaborate a better social presentation of its service or to withdraw from these affiliates.

Side notes:
- Super Affiliates not behave as expected
- Fraudulent Behavior
- Competition

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[79] C. f. KANE ET AL. 2014

5. Conclusions

5.1. Managerial Implications

Affiliate marketing practitioners tend to define operations by typical KPIs, such as LEADS and SALES, and most merchants prefer affiliates that appear in close proximity to their own offer or that earn the highest scores on typical KPIs. But an affiliate partnership grows over the course of the relationship, which suggests that a merchant needs control variables to predict the future behavior of existing affiliates and identify good potential affiliates. By clustering 329 affiliates from two European affiliate networks, we identified five relevant types of affiliates. Four of these clusters reflect specific pairings of partnership type and website focus, the so called cancelled and average affiliates. One cluster mixes these traits and reflects the super affiliates. All these affiliates engage in social activities. However, the smallest cluster type not behaves like super affiliate cluster; it generates no sales, despite the high volume of LEADS, CLICKS, and ad-related variables. Instead, it seems to serve as a funnel for users, guided by acquaintances or newspaper ads. These findings offer several insights for affiliate marketing practitioners.

Short Summary

First, activity in social networks is essential for existing and prospective affiliates, as demonstrated by its prominence in nearly every cluster. Cancelled affiliates engaged in less social network activities than average affiliates, which suggests that affiliates must exert a certain level of activity to establish a reliable partnership. Affiliates with very high social activity may create high competition between merchants, but in exchange, they have more LEADS, and therefore more users' who get to know the merchants' services or products. Competition is a concern though, because users compare merchants on social networks, and the probability of losing a user to another merchant increases with greater competition. A merchant that wants to increase solely its LEADS is primarily the type that should be interested in affiliates with strong social networks.

Merchants should look for Affiliates with social networks

Affiliates with a high social activity might indicate high competition

Second, merchants should cooperate with affiliates with a divergent website focus. Non–education-related affiliate websites generated the same revenues as their education-focused counterparts, but with half the number of affiliates and more FOLLOWERS. Thus, a single sales channel, through an education-related website, is absolutely not sufficient, especially considering that the trade-off for a more related focus is greater competition.

Merchants should cooperate with different website priorities

Merchants
should use
search engines
to amplify affil-
iate marketing

Third, merchants should strengthen the role of a search engine in the user journey more precisely. While acquaintances can sometimes initiate an affiliate marketing search, search engine advertising and optimization are dominant channel touchpoints for all users. Thus, additional campaigns in search engines might help users to remind or recognize the merchant when comparing different offers on an affiliate website.

Merchants
should check
for competition
and not solely
KPIs

Fourth, the merchant in our study cut ties with affiliates that exhibited minimal social activities and ad usage, despite the revenue they generated. We recommend instead that merchants rely on additional variables to control their affiliates' behavior and performance, including the number of other merchants on an affiliate's website and not solely KPIs.

5.2. Limitations and Further Research

Lack of
business models

In addition to its contributions to academic research and utility for practice, our study contains some limitations. In particular, we lack information about the affiliates' business models. Affiliates clearly pursue different activities with their websites. For example, a price comparison site has different goals than a blog. An affiliate with a blog can include personal recommendations when forwarding users to a merchant's landing page, but a banner ad stand for itself. Further research should consider the distinct business models and associated recommendation behavior demonstrated by affiliates.

Lack of
specific recom-
mendation
behavior

Lack of
user navigation

We also lack information about user navigation. While the merchant uses other marketing instruments too, there is a chance that a user had contact with more than one advertising channel during the buying or search process. Additional research could track users according to their navigation between affiliate websites and on social networks.[80] This information could be essential, especially if an affiliate promotes the merchant's offering in a social network, and the user switches among several social networks and merchant websites. If practitioners and affiliate networks included more information about affiliates' and users' behaviors in other channels, it would help advance academic research.

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[80] C. f. MOE 2003; BENEVENUTO ET AL. 2012.

Bogus LEADS represent another potential limitation. Potential fraud is a legitimate reason to terminate a relationship, and it would be interesting to identify whether any of the terminated partners in our study produced bogus LEADS. For example, affiliates in cluster T1 might have been terminated because they tried to cheat the merchant, or because their performance was poor. But, bogus LEADS are hard to detect, because managers need to check user LEADS manually and have to deal with technical issues like cookie-stuffing.[81] Thus, it is obvious that many of the further described affiliate partnerships e. g. in cluster T3, were cancelled because of a strong suspicion, but no final affirmative proof. We encourage further research to integrate the view of bogus attempts in affiliate marketing.

Lack of bogus leads

Lack of general bogus behavior

Finally, our unique data set refer to a high-involvement service with a specific payment model. It would be interesting to test our approach in other segments, such as fast moving consumer goods, and for other payment models, such as per item sales (e.g., clothes) or contracts (e.g., mobile phones). In general, affiliate marketing research needs more dynamic research approaches that incorporate the natural entrances and exits of affiliates from the portfolio, together with their behavior in social networks.

Lack of further consumer goods and other payment models

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[81] C. f. EDELMAN 2009.

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The Authors of the Research Paper

Univ.-Prof. Dr. Rainer Olbrich

Rainer Olbrich, born in 1963 in Olsberg (Germany), finished his Abitur (German higher education entrance qualification) in 1983 in Winterberg.

At the University of Münster, he then pursued a degree in business administration, earning his Diplom-Kaufmann (German business administration degree) in 1988. By 1992, he had received his doctorate in business administration from the University of Münster, where he also habilitated in 1997. Then in 1997, he became Professor of Marketing at the University of Hagen, where he currently holds the Chair of Marketing.

Parallel to his academic career, Rainer Olbrich worked for a German consultancy focusing on marketing, strategy, and portfolio projects from 1985 to 1989. He has worked for more than 25 years in the education sector, on various projects, and as an expert for leading German companies, organizations, and public institutions. He also served as a prorector for research, dean, speaker of deans, and vice dean.

His fields of research interest pertain mainly to consumer goods marketing, retail marketing, and marketing controls. Rainer Olbrich is the author of several textbooks, as well as a long list of journal articles. A summary of his publications is available on the website of the Chair of Marketing (http://www.fernuni-hagen.de/MARKETING/).

Dipl.-Ök. Patrick Bormann

Patrick Bormann, born 1983 in Düsseldorf (Germany), finished his Abitur (German higher education entrance qualification) in 2006 in Ratingen.

During his school days, he finished a beyond three-year apprenticeship as a nationally certified information technology assistant. At the University of Wuppertal, he pursued a degree in economic science earning his Diplom-Ökonom (German university degree comparable to the Master of Science) in 2011. His major fields of study were marketing and information systems. Also he was a scholarship holder of the Hermann-and Helen-Wilden foundation.

Moreover, he finished several internships in the fields of marketing and information technology, for example at symantec Deutschland GmbH in Ratingen and Daedalic Entertainment GmbH in Hamburg. He gathered additional experience as a business consultant in the fields of e-mail marketing at the DocCheck AG in Cologne, the leading healthcare online-service provider in Europe.

Since 2011 he is a research assistent at the University of Hagen for the Chair of Marketing. His fields of research interest pertain strategic and brand-related issues in the area online-marketing, social media, consumer behavior and mainly affiliate-marketing. Thus, he examines possible opportunities of infuence on the economically success of a merchant in the affiliate-merchant-relationship.

Dr. Christian Holsing

Christian Holsing, born in 1978 in Lübbecke (Germany), finished his Abitur (German higher education entrance qualification) in 1997. In addition, he finished a two-year apprenticeship in wholesale and foreign trade at EDEKA and pursued a degree in business administration at the Universities of Vienna and Bielefeld, earning his Master's degree in 2006.

From 2006 to 2007 he worked as a marketing consultant at IRI Worldwide, a leading business consultancy for retail and consumer goods. For the last fifteen years he supported companies in terms of strategy, e-commerce and online-marketing as a freelance consultant. He gathered additional experience through building an own online shop from scratch. Furthermore, he has project-related work experience for the Think Technology Group in London, Eckes-Granini, and Telefónica.

From 2007 to 2012 he was a doctoral candidate at the Chair of Marketing, University of Hagen, Germany. There he achieved his doctoral degree in 2012. The subject of his thesis is as follows: "Kaufverhaltensforschung in Social Shopping Communities – dargestellt unter Berücksichtigung einer Logfile-Analyse". Furthermore, he was jointly responsible for the research project ‚Social Commerce' in cooperation with one of the largest online-retailers worldwide. The results of his research were published on several conferences (e.g. 'International Conference on E-Commerce' in Singapore and Finland) and in well-known journals (e.g. ‚International Journal of Electronic Commerce').

From 2013 to 2016 he worked for Lynx Consulting Group (Senior Consultant, Head of 'Strategy & Marketing', and Head of Business Unit 'E-Commerce & Digital Marketing'). Beyond that, he is a member of the supervisory board of the DomainBoosting AG and founder of 24h-PflegeCheck.de

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