

Getting a Job via Career-oriented Social Networking Sites: The Weakness of Ties

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Abstract

By asking users of career-oriented social networking sites I investigated their job search behavior. For further IS-theorizing I integrated the number of a user's contacts as an own construct into Venkatesh's et al. UTAUT2 model, which substantially rose its predictive quality from 19.0 percent to 80.5 percent concerning the variance of job search success. Besides other interesting results I found a substantial negative relationship between the number of contacts and job search success, which supports the experience of practitioners but contradicts scholarly findings. The results are useful for scholars and practitioners.

1. Introduction

More and more companies such as [IBM](#) or [Microsoft](#) make use of social media in order to search for and recruit new employees [1]–[4]. There is a tremendous increase in professional company profiles on [LinkedIn](#), [XING](#) and similar career-oriented online social network sites (CSNS). Despite some specific challenges when contracting employees electronically [5]–[8] the CSNS figures, such as 380 mio. registered LinkedIn members, 4 mio. company profiles on LinkedIn, 15 mio. XING members, and 200,000 company profiles on XING, show the significant recruiting potential of CSNS. In order to clarify the CSNS conception within the Social Computing area [9] I define CSNS as a social networking site (SNS, [10]) the primary purpose of which is career-oriented (e.g. finding new jobs or employees).

It is surprising that the effect of the number of contacts in terms of job search success has not been sufficiently theorized in prior CSNS research on an individual user level – although Granovetter stressed the important role of contacts in his famous book “*Getting a Job: A Study of Contacts and Careers*” [11] many decades ago. Prior CSNS research took place on

a macro level. E.g., from a value calculation point of view it is coherently argued that the value of a CSNS is primarily based on its membership figures (cf. value-growth curves such as Metcalfe's law, Reed's law, Sarnoff's law, Zipf's law). These scholars argued for an increased (social) network value with every additional contact [12]. In addition, positive relations of social media metrics such as membership figures and firm equity values were found [13].

Considering the importance of membership figures on the CSNS macro level it is surprising that on the CSNS micro level the (dynamic) role of the number of (direct) contacts did not play a major role in research in the past. At first glance it also sounds plausible that an increased number of contacts (as the most common network centrality measure [14]–[17]) is better for a member in terms of career-oriented success. Confirming this speculation, prior research on offline career-oriented networks found positive relationships between network centrality and career success [18,19] as well as individual [20] and group performance [21]. In addition, scholars argued that “*SNS make a larger contact pool available to their members and allow them to easily manage and maintain virtually unlimited numbers of contacts by granting access to the long tail of social networking – an additional pool of contacts that is inaccessible via traditional networking.*” [22, p.209]. Furthermore, prior research found evidence that the number of recruiters' contacts implies greater success in recruiting [23]. However, professional “*recruiters seem do distrust the number of contacts [of an applicant] as a sort of 'noisy' information*” [24, p.6] and other scholars from human resources such as Wanberg et al. [25] found no relationships between networking centrality and reemployment success.

Despite this interesting research gap there is to the best of my knowledge no CSNS specific investigation that empirically analyzes the relationship between job-seekers' centrality and success in terms of getting job offers.

That is why in this paper I empirically analyze the relationship between the number of CSNS contacts a person has (as the most important centrality measure [14]) and CSNS outcome in terms of getting job offers, by integrating the number of contacts as an own construct into Venkatesh's et al. UTAUT2 model [26].

Using this research I aim to contribute to the following research questions (RQs):

RQ1: What is the role of the number of contacts in terms of getting job offers via CSNS?

RQ2: What drives the intention to use CSNS for a job search?

The most important contributions from this work are:

1. By integrating the number of contacts as an own construct in UTAUT2, its predictive quality substantially rises from 19.0 percent to 80.5 percent, (RQ1).
2. There is a substantial negative relationship between the number of contacts and job search success, which confirms the gut instinct of professional headhunters (cf. [24, p.6]) and emphasizes the senselessness of simply "collecting contacts" [27], (RQ1).
3. Resources and knowledge about job search functions in CSNS mainly drive job search intentions, which confirms results from new institutional economics about job search markets, e.g. [28,29] (RQ2).
4. In contrast to prior research from human resources concerning offline job search behavior, e.g. [30], I found evidence that habit plays an important role in building job search intention in CSNS, (RQ2).

My results are useful for scholars and practitioners. For scholars I will show potential for further IS-theorizing of (C)SNS usage. In addition, while past research has focused on general motives for job search intention, e.g. [31], there is not much knowledge concerning the usage of C(SNS) for job search activities. Through the work I shed light on C(SNS) usage for the job search, which is also fruitful for both CSNS operators and users. Operators can improve CSNS by improving the job search functions and its explanations. Users benefit from the insight that simply "collecting contacts" [27] does not make sense in terms of getting job offers. This insight is interesting because it was found that SNS users primarily construct their network on the basis of expectations regarding the value of networking [32].

The paper is organized as follows: Next I derive the hypotheses from existing theories and develop the

research model. After that the research methodology, including the sampling strategy and all measurements are presented before the results, including the sample characteristics and the structural model, are shown. Finally, the conclusion is presented, including limitations and future research.

2. Research Background, Research Model and Hypothesizing

A very promising development in electronic human resource management is the incorporation of (C)SNS [33]. Envisioned thirty years ago by Macdonald [34], job search via (C)SNS has actually emerged to an important application channel [35]–[37]. Nowadays scholars and practitioners coherently argue the increased importance of (C)SNS for job search [1]–[3,38].

Prior IS research theorized the antecedents of the intention to use SNS. Research from human resources scholars theorized the antecedents of job offer success. Research on technology acceptance in the social media and consumer context has been dominated by the Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM+), Unified Theory of Acceptance and Use of Technology (UTAUT+), IS Continuance Model (CM), Multi Attribute Utility Theory (MAUT) [39]. The most prominent models used for SNS analysis were TAM+, e.g. [40], and UTAUT2, e.g. [41]. Since Venkatesh's et al. UTAUT2 model "extends the unified theory of acceptance and use of technology (UTAUT) to study acceptance and use of technology in a consumer context" [26, p. 157], I integrate the knowledge from human resources in terms of job offer success into Venkatesh's et al. UTAUT2 model [26] in order to map the intention to use a CSNS for a job search as well as to model the relationship between intention to use and perceived system usage for a job search. Based on this modeling I further extend the model by the effects of perceived system usage on the number of contacts and job offer success and consequently derive the hypotheses. Please note that intention to use a CSNS refers to usage for job searches, not usage per se.

2.1. Antecedents of the Intention to Use Social Networking Sites for a Job Search

Plummer and Hiltz [42,43] proposed a research framework to explain Behavioral Intention concerning job search via SNS. They found substantial effects

of Performance Expectancy and Effort Expectancy on Behavioral Intention. These influences were already theorized by Davis [44] and Venkatesh et al. [26,45] within TAM(++) and UTAUT(2). That is why I hypothesize:

H₁: *Performance Expectancy will be positively associated with Behavioral Intention.*

H₂: *Effort Expectancy will be positively associated with Behavioral Intention.*

Tianhui et al. [46] analyzed how SNSs affect job choice intention and found a moderate peer group influence. This kind of Social Influence was already conceptualized by Venkatesh et al. [26]. I hypothesize:

H₃: *Social Influence will be positively associated with Behavioral Intention.*

New institutional economics theorized that sufficient resources and knowledge about systems, processes and market functions are critical components for the success of both the individual and the whole economy [47]–[49]. That applies in particular to a job search [28,29]. Venkatesh et al. [26] theorized the impact of sufficient resources and knowledge in terms of system usage on Behavioral Intention. Thus I hypothesize:

H₄: *Facilitating Conditions will be positively associated with Behavioral Intention.*

Brecht and Eckhardt [50] found that humanities graduates use SNSs predominantly for entertainment purposes. Since general technology acceptance research also largely theorized the importance of Hedonic Motivation in terms of using IS [26,51,52] I consequently hypothesize:

H₅: *Hedonic Motivation will be positively associated with Behavioral Intention.*

Venkatesh et al. theorized that “*the cost and pricing structure may have a significant impact on consumers’ technology use* [26, p.161]. Consumers usually bear the monetary cost of such use [53]. Following Venkatesh et al. I define Price Value as “*consumers’ cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them* [26, p.161] and therefore hypothesize:

H₆: *Price Value will be positively associated with Behavioral Intention.*

IS scholars [54,55] and psychologists [56] have largely theorized the influence of Habit on Behavioral Intention. LaRose and Eastin [57] showed that internet habit strength will be directly related to internet usage intention. Habit was also theorized as important for social media usage intention [58,59]. I consequently theorize:

H₇: *Habit will be positively associated with Behavioral Intention.*

2.2. Antecedents of Job Offer Success

IS acceptance research, e.g. [26,44,45], has coherently theorized a positive relation between Behavioral Intention and Usage Intensity. That is why I hypothesize:

H₈: *Behavioral Intention will be positively associated with Usage Intensity.*

Saks [60] found that active job search intensity predicts job offers. Also the meta-analysis of Kanfer and colleagues [61] revealed a moderate positive relationship between job search behavior and the number of job offers. Against this background I hypothesize:

H₉: *Behavioral Intention will be positively associated with Job Offer Success.*

H₁₀: *Usage Intensity will be positively associated with Job Offer Success.*

Research on the impact of Usage Intensity on forming social ties has generated conflicting results [62]. Kraut et al. [63] coined the phrase “*Internet paradox*” meaning that increased internet usage decreases the size of a users’ social network. In contrast, Zhao [62] revealed that “*social users of the Internet have more social ties than nonusers do*” [62, p.844]. Gonçalves et al. [64] also found a positive relationship between SNS usage and the Number of Contacts. Robinson and Martin [65] also found contradictory results. While reading, for example, was associated with increased IT media use, the IT media usage level was not consistently correlated with levels of socializing or other social activities [65]. Since Kraut et al. [66] showed that the negative effects reported in [63] dissipated over time and the majority of scholars found positive consequences in SNS usage concerning the building and maintaining of social contacts. Thus I hypothesize that:

H₁₁: *Usage Intensity will be positively associated with the Number of Contacts.*

At first glance it also sounds plausible that an increased number of contacts (as the most common network centrality measure [14]–[17]) is better for a member in terms of career-oriented success. Confirming this speculation, prior research on offline career-oriented networks found positive relationships between network centrality and career success [18,19] as well as individual [20] and group performance [21]. An increased number of contacts increases the probability of bridging structural holes [67] and of also having more weak ties [68]. “*In this sense, networks can help us cover more space; they can enable us ’to be there without being there’*” [69, p.823]. Furthermore, since various value-growth curves (Metcalf’s law, Reed’s

law, Sarnoff’s law, Zipf’s law) coherently argue for an increased (C)SNS value with every additional contact [12], also the value calculation point of view leads to the belief in a positive relationship between the number of contacts and the number of job offers. In addition, most of the practitioners loudly affirmed that there were greater job opportunities due to an increased contact pool in CSNS, e.g. [1,2]. “*SNS make a larger contact pool available to their members and allow them to easily manage and maintain virtually unlimited numbers of contacts by granting access to the long tail of social networking – an additional pool of contacts that is inaccessible via traditional networking.*” [22, p. 209]. However, some “*recruiters seem do distrust the number of contacts as a sort of ‘noisy’ information*” [24, p.6] in CSNS and also some scholars did not found any relationship between networking centrality and (re-)employment success in offline career-oriented SNS, e.g. [25]. Hence, the question arises if the Number of Contacts is important in terms of getting job offers or is it just “*the illusion of community*” [70]? Since the majority of scholars theorized a positive relationship between the Number of Contacts and Job Offer Success in offline career-oriented SNS I will evaluate this for CSNS and consequently hypothesize:

H₁₂: *Number of Contacts will be positively associated with the Job Offer Success.*

The research model is shown in figure 1.

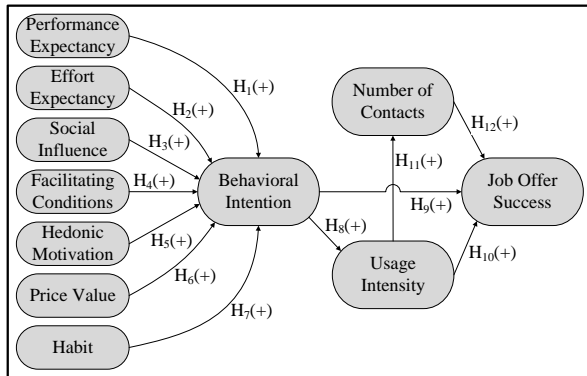


Figure 1: Research Model

3. Methodology

3.1. Sampling strategy

I recruited *working professionals* who studied extra-occupationally at our university. The participants were asked electronically to take part in a survey concerning social networks. The call for participation was sent

out with a link to the online questionnaire via our Germany-wide university.

3.2. Measurements

All constructs of the research model (figure 1) were operationalized by proven and established measurement instruments (see table 1). Each item, with the exception of Number of Contacts, was measured using a 7-point Likert scale. Furthermore I captured sociodemographic data for each participant.

Constr.	Abbr.	Item text	Load.	M	S.D.	Ref.
Performance Expectancy	PE-1	A CSNS is not useful for me in terms of finding new jobs. [rev.]	.978	2.18	1.50	Acc. to [26]
	PE-2	I am more effective by using a CSNS in order to find new jobs.	.966	4.79	1.56	Acc. to [26]
Effort Expectancy	EE-1	Job search with CSNS is clear and simple.	.948	4.82	1.34	Acc. to [26]
	EE-2	It is easy for me to get experienced with CSNS.	.964	5.14	1.35	Acc. to [26]
Social Influence	SI-1	People who influence me think that I should use CSNS for job search.	.925	3.58	1.71	Acc. to [26]
	SI-2	People whose opinions that I value prefer that I should use CSNS for job search.	.958	4.53	1.55	Acc. to [26]
Facilitating Conditions	FC-1	I have not the necessary resources to find jobs via CSNS. [rev.]	.947	1.68	1.12	Acc. to [45]
	FC-2	I have the necessary knowledge to find jobs via CSNS.	.861	5.42	1.30	Acc. to [45]
Hedonic Motivation	HM-1	Job searching with CSNS is enjoyable.	.949	4.58	1.39	Acc. to [26]
	HM-2	I am pleased to search for job with my CSNS.	.826	3.95	1.53	Acc. to [26]
Price Value	PV-1	Job search via CSNS has a bad price-performance ratio. [rev.]	.878	2.64	1.69	Acc. to [26]
	PV-2	The current price-performance ratio of CSNS in terms of job search is fine.	.952	4.69	1.60	Acc. to [26]
Habit	HA-1	Job hunting with CSNS has become a habit for me.	.801	4.32	1.86	Acc. to [26]
	HA-2	Job hunting with CSNS has become normal for me.	.954	4.86	1.72	Acc. to [26]
Behavioral Intention	BI-1	I do not intend to use CSNS for job hunting. [rev.]	.887	1.97	1.44	Acc. to [71]
	BI-2	I will always try to search for jobs via CSNS.	.875	5.12	1.61	Acc. to [71]
Usage Intensity	UI-1	How often do you use a CSNS for job search [never - daily]?	.898	3.43	1.37	Acc. to [26]
	UI-2	How often do you apply via CSNS [never - daily]?	.929	2.28	1.18	Acc. to [26]
Number of Contacts ¹	NC-1	How many direct contacts do you have on XING ² ?	-. ¹	112	215	Acc. to [10]
	NC-2	How many direct contacts do you have on your internal SNS?	-. ¹	100	154	Acc. to [10]
Job Offer Success	JS-1	How often do you get job offers by your personal network via CSNS [never - daily]?	-. ¹	3.52	1.55	Acc. to [61]
	JS-2	How often do you get job offers by headhunters via CSNS [never - daily]?	-. ¹	3.09	1.57	Acc. to [61]

Table 1: Measurement items for constructs; ¹formative; ²XING is an important business-oriented online social network in Europe.

4. Results

4.1. Sample characteristics

Data were collected via an online-based questionnaire. 524 completed questionnaires were received. After removing one invalid questionnaire which consistently showed an equal answer pattern (maximum was always clicked), 523 questionnaires (~ 99.8%) were used within the analysis. The remaining participants were aged from 16 to 52 years (M=26.9, S.D.=4.9). 271 (~ 51.8%) of the test persons were female, 251

male. One participant did not answer the question concerning sex.

354 participants used XING and 97 individuals used an internal (company) SNS. 222 participants actively used its CSNS to find new jobs.

4.2. Evaluation of the Measurement Model

Following the recommendations of Ringle et al. [72] I report item wording, scales, scale means and standard deviations for all measures (table 1):

	AVE	α	CR	PE	EE	SI	FC	HM	PV	HA	BI	UI	NC	JS
PE	.945	.942	.971	.972										
EE	.914	.906	.955	.637	.956									
SI	.886	.874	.940	.346	.212	.941								
FC	.819	.789	.900	.141	.748	.141	.905							
HM	.792	.755	.883	.619	.686	.611	.393	.890						
PV	.839	.817	.912	.748	.557	.011	.443	.463	.916					
HA	.776	.737	.873	.716	.574	.353	.422	.530	.676	.881				
BI	.776	.712	.874	.767	.733	.254	.817	.525	.599	.694	.881			
UI	.834	.802	.910	.476	.246	.323	.210	.309	.305	.511	.372	.913		
NC	-.1	-.1	-.1	.166	.000	.035	-.078	.145	-.029	-.049	.028	.430	-.1	
JS	-.1	-.1	-.1	-.118	.314	.125	.148	.116	-.052	.334	.140	-.261	-.698	-.1

Table 2: Quality Criteria of the Measurement Model: Average Variance Extracted (AVE), Cronbach's (α), Composite Reliability (CR), Diagonal contains $\sqrt{\text{AVE}}$ values

Please note that within the measurement model I use 9 constructs with reflective indicators and 2 formative constructs (cf. [73]).

4.2.1. Reflective Constructs. Following the guidelines of Hair et al. [74] and Urbach and Ahlemann [75] I report internal consistency reliability, indicator reliability, convergent validity and discriminant validity for the evaluation of the reflective measurements.

Internal Consistency Reliability: The internal consistency of all constructs is given as both values, Cronbach's α and Composite Reliability CR, were greater than .7 for each construct (see table 2, cf. [76,77]).

Indicator Reliability: The variance of a latent construct extracted from a specific item should be greater than .5 which means that the factor loadings of the indicators should be above .7(07) [78,79]. This condition is fulfilled for all indicators with no exception (see table 1). In addition, the factor loadings were all significant at a $p < .001$ level (nonparametric bootstrapping procedure according to Efron and Tibshirani [80] with 5,000 samples).

Convergent Validity: In order to evaluate the convergent validity I used the Average Variance Extracted (AVE) values of each reflective construct. In my dataset all AVEs were above .5 (see table 2) which indicates convergent validity [74].

Discriminant Reliability: The discriminant validity check in terms of the cross loadings criterion according to Chin [81] was also successful in my dataset. Finally, the Fornell-Larcker criterion [82] is also fulfilled as $\sqrt{\text{AVE}(\text{construct}_i)} > \text{CORR}_{\text{construct}_i, \text{construct}_j}$ (table 2).

4.2.2. Formative Constructs. Following the guidelines of Henseler et al. [83] I report indicator validity and construct validity for the evaluation of the formative constructs.

Indicator Validity: Each formative indicator was relevant due to a significance level of $p < .001$ (non-parametric bootstrapping procedure according to Efron and Tibshirani [80] with 5,000 samples) and absolute path coefficients above .2 (cf. [81]). In addition, I can report that multicollinearity is not an issue since variance inflation factors (VIFs) were below 5 (cf. [74, pp. 125]).

Construct Validity: Discriminant validity was also sufficient since the interconstruct correlations between the formative constructs and all other constructs were below .71 (cf. [84]).

In summary I can state that the measurement model is valid (cf. [74]).

4.3. Structural Model Results

To investigate the latent structure of the constructs and their causal relations, I conducted a structural equation model using smartPLS [85], which provides very robust model estimates, regardless of the distributional properties [74, p. 22]. The model used the indicators as described in table 1. Significance level were assessed by the bootstrapping algorithm of smartPLS [85] with $n=5,000$ samples.

Model Validity: Through my model shown in figure 2 I reached excellent quality measures and can strongly explain Job Offer Success (JS) ($R^2_{\text{JS}}=.805$). Moreover, I evaluated the predictive relevance Q^2 [86,87] of the model. Using the blindfolding procedure of smartPLS [85] I calculated Q^2 values larger than zero for the reflective endogenous latent variables in my model ($Q^2_{\text{BI}}=.654$, $Q^2_{\text{UI}}=.272$) which indicates the model's predictive relevance [74]. Finally post-hoc power analyzes also revealed a very good statistical power value of 1.0 ($\gg 0.80$, cf. [88, p. 473]).

Model Analysis: What is really interesting is the substantial negative effect of the Number of

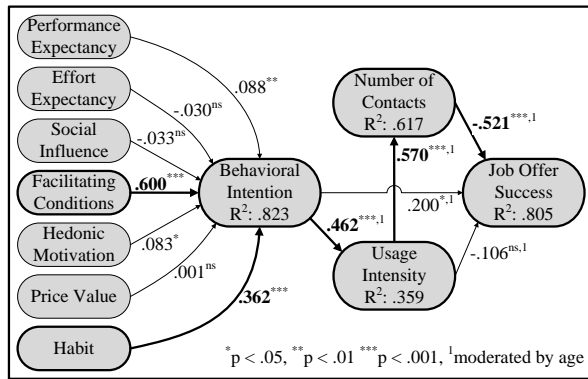


Figure 2: SEM Results

Contacts on Job Offer Success ($p_{NC-JS} = -.521$). The Number of Contacts is sufficiently explained by the Usage Intensity ($R^2_{NC} = .617$, $p_{UI-NC} = .570$) which in turn is predicted by the Behavioral Intention ($R^2_{UI} = .359$, $p_{UI-NC} = .462$). The Behavioral Intention is mainly influenced by Facilitating Conditions and Habit ($p_{FC-BI} = .600$, $p_{HA-BI} = .362$).

I found that the Number of Contacts partially mediates the effect of Usage Intensity on Job Offer Success (Sobel test [89], $p < .001$). Please note that the full mediator effect of Number of Contacts was not achieved since the direct effect of Behavioral Intention on Job Offer Success still remained significant, though at a lower level ($p < .05$).

When deleting the 'Number of Contacts' construct the model substantially lost predictive quality. This reduced model reached an explanation of 19 percent ($R^2_{JS} = .190$) which means only a weak effect [75, p. 21]. Also the path coefficients were only small-medium [81,90].

I found that the Usage Intensity partially mediates the influence of Behavioral Intention on Job Offer Success (Sobel test [89], $p < .001$). If we also delete this mediator, the model power in terms of JS variance is even smaller ($R^2_{JS} = .126$).

5. Discussion

What is the Role of the Number of Contacts in terms of Getting Job Offers via Career-oriented Social Networking Sites (RQ1)?: First of all I can report that by integrating the number of contacts as an own construct in UTAUT2, its predictive quality substantially rises from 19.0 percent to 80.5 percent. However, as stated within the structural model results section, the counterproductive role of Number of Contacts in terms of getting job offers ($p_{NC-JS} = -.521$) is surprising. Previously, Granovetter stressed

the important role of contacts for getting jobs in his famous book "*Getting a Job: A Study of Contacts and Careers*" [11] many decades ago. A lot of other scholars also confirmed the value of weak and strong ties, in particular for getting job offers [67,68,91,92] and also that shareholders act on the basis of "*The more, the better*". The only doubt came from practitioners, especially from professional headhunters, e.g. [24, p. 6] and Wanberg et al. [25], stating that the number of contacts is negligible. While Wanberg's et al. work [25] was related to unemployed job seekers and offline carrier-oriented SNS, this work is related to online CSNS and is not restricted to a specific group, i.e. unemployed job seekers. Based on the results I can support the gut instinct of professional headhunters and will follow Donath's and boyd's [27] call that simply "*collecting contacts*" [27] does not make sense. This result is of importance for the evolution of online social networks [93]. In summary I found no support for H₁₂.

I also found no support for H₁₀ since the relationship between Usage Intensity and Job Offer Success was negative in my investigation. However, I can support H₈, H₉ and H₁₁.

What drives the Intention to Use Career-oriented Social Networking Sites for Job Search (RQ2)?:

In contrast to prior general technology acceptance research, e.g. [26,44,45], I found no positive relationship between Effort Expectancy nor Social Influence nor Price Value and Behavioral Intention (no support of H₂, H₃ and H₆). The prior theorized positive influences of both Performance Expectancy and Hedonic Motivations on Behavioral Intention were also evident in my investigation concerning significance but only at a negligible effect size level ($f^2_{PE} = .006$, $f^2_{HM} = .017$, cf. [81,90]). That is why I can also not support H₁ and H₅.

However I found a strong impact of Facilitating Conditions on Behavioral Intentions (support of H₄). This result confirms the major role of sufficient resources and knowledge prior theorized in economics [47]-[49], human resources [28,29] and IS research [26,94]-[97].

My results also show that Habit substantially forms Behavioral Intention in terms of job search via CSNS (support of H₇). But this is surprising and in contrast to prior knowledge from offline job search. Prior research argued that "*job search typically is a nonroutine and complex task, for which little automatic script structures are available, it requires continuous conscious processing and self-regulation*" [30, p. 9]. Cognitive processes in offline job search comprises a behavioral phase of goal striving, directional maintenance, volitional control, maintaining of the planned activities

as well as reflection and revision [30] – indicating a high level of conscious processing. However, the substantial influence of Habit on Behavioral Intention which I found in my investigation was theorized in general IT use [54,55,57] and social media usage [58,59]. This result indicates that a job search as a nonroutine and complex task may in principle be potentially transformed to an automatic unconscious procedure by means of CSNS usage (cf. [56]).

Implications: My investigation shed light on CSNS usage for the job search and the study results are useful for scholars and practitioners. From a theoretical point of view it is interesting that only Facilitating Conditions and Habit are the (substantial) predictors of Behavioral Intention. In addition, the counterproductive role of Number of Contacts for Job Offer Success is interesting for further IS theorizing. This was not theorized previously but was often reported by practitioners, e.g. [24, p.6]. Furthermore, my results are also fruitful for both CSNS operators and users. Operators can enhance CSNS by improving the job search functions and its explanations. The study revealed the need for sufficient knowledge and resources to form a users' intention to use a CSNS for a job search. That is why I recommend CSNS operators to systematically assess the user's knowledge related problems (e.g. by means of the approach of Deng and Chi [94]) in order to make CSNS use habitual for a user. Please remember that Facilitating Conditions and Habit are the substantial factors to form the user's intention to use a CSNS for job search. Users benefit from the insight that simply “collecting contacts” [27] does not make sense in terms of getting job offers. This insight is interesting for users because it was found that SNS users primarily construct their network on the basis of expectations regarding the value of networking [32].

6. Conclusion

In this paper I empirically analyzed the relationship between the number of CSNS contacts a person has (as the most important centrality measure [14]) and CSNS outcome in terms of getting job offers by integrating the number of contacts as an own construct into Venkatesh's et al. UTAUT2 model [26]. By asking 523 participants and subsequently analyzing by means of structural equation modeling I found that due to the integration of the number of contacts as an own construct in UTAUT2 its predictive quality substantially rises from 19.0 percent to 80.5 percent. In addition, I found a substantial negative relationship between the number of contacts and job search success, which

supports the experiences of practitioners [24, p.6] and questions the value propositions of all career-oriented social networking sites. Furthermore, I revealed that resources and knowledge about job search functions in CSNS mainly drive job search intentions, which confirms speculation from new institutional economics about job search markets, e.g. [28,29]. In addition, in contrast to prior research from human resources concerning offline job search behavior, e.g. [30], I found evidence that habit also plays an important role in building job search intention in CSNS.

6.1. Limitations

The main limitation of the study concerns the operationalization of the centrality measure, i.e. Number of Contacts. There is no doubt that the number of contacts is the most common centrality measure, cf. [14], but there are much more sophisticated ones, cf. [17,91].

Another limitation is related to the measurement of the Job Offer Success concept. Since it is neither possible to retrieve the exact number of job offers from the XING application nor from its API I decided to operationalize this construct using two items measuring perceived job offer success. However, this measure could be (slightly) biased because psychological research has documented systematic errors in all retrospective evaluations, cf. [98].

Furthermore, I controlled the sample only by age and gender. As shown in figure 2 the relationships to the outcome variables were moderated by age. However, I did not control for other variables such as education, duration of unemployment, financial status, etc.

6.2. Future research

Future research should investigate the relationship between the number of contacts and job offer success in more detail, i.e. by adding constructs concerning the contact collecting attitudes and behavior (e.g. senselessly collecting contacts versus a conscious approach).

Future work should also investigate the role of other network centrality measures [17,91] concerning the impact of Job Offer Success in CSNS. For instance, using a survey data of 109 unemployed job seekers, Garg and Telang [92] found that weak ties are especially helpful in generating job leads but it is the strong ties that play an important role in generating job interviews and job offers. That is why the use of other centrality measures than the number of contacts could be fruitful for further IS-theorizing. In addition, the initial evidence that CSNS can transform job search

activities as a nonroutine and complex task into automatic unconscious processes could also be fruitful for subsequent investigations.

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References

- [1] R. Doherty, "Getting social with recruitment," *Strategic HR Review*, vol. 9, no. 6, pp. 11–15, 2010.
- [2] S. A. Madia, "Best practices for using social media as a recruitment strategy," *Strategic HR Review*, vol. 10, no. 6, pp. 19–24, 2011.
- [3] X. Zhou, Y. Xu, Y. Li, A. Josang, and C. Cox, "The state-of-the-art in personalized recommender systems for social networking," *Artificial Intelligence Review*, vol. 37, no. 2, pp. 119–132, 2012.
- [4] R. Buettner, "Personality as a predictor of business social media usage: An empirical investigation of XING usage patterns," 2015, Presentation at VHB '15 Conference, Vienna, Austria, May 27-29, unpublished.
- [5] R. Buettner, "A Systematic Literature Review of Crowdsourcing Research from a Human Resource Management Perspective," in *HICSS-48 Proc.*, 2015, pp. 4609–4618.
- [6] R. Buettner and J. Landes, "Web Service-based Applications for Electronic Labor Markets: A Multi-dimensional Price VCG Auction with Individual Utilities," in *ICIW 2012 Proc.*, 2012, pp. 168–177.
- [7] R. Buettner, "The State of the Art in Automated Negotiation Models of the Behavior and Information Perspective," *ITSSA*, vol. 1, no. 4, pp. 351–356, 2006.
- [8] R. Buettner, "A Classification Structure for Automated Negotiations," in *IEEE/WIC/ACM WI-IAT 2006 Proc.*, 2006, pp. 523–530.
- [9] Y. Li and K. D. Joshi, "The State of Social Computing Research: A Literature Review and Synthesis using the Latent Semantic Analysis Approach," in *AMCIS '12 Proc.*, 2012, paper 13.
- [10] d. m. boyd and N. B. Ellison, "Social Network Sites: Definition, History, and Scholarship," *Journal of Computer-Mediated Communication*, vol. 13, no. 1, pp. 210–230, 2008.
- [11] M. S. Granovetter, *Getting a Job: A Study of Contacts and Careers*, 2nd ed. Univ. of Chicago Press, 1995.
- [12] B. Briscoe, A. Odlyzko, and B. Tilly, "Metcalfe's law is wrong - communications networks increase in value as they add members-but by how much?" *IEEE Spectrum*, vol. 43, no. 7, pp. 34–39, 2006.
- [13] X. Luo, J. Zhang, and W. Duan, "Social Media and Firm Equity Value," *Information Systems Research*, vol. 24, no. 1, pp. 146–163, 2012.
- [14] M. E. Shaw, "Group Structure and the Behavior of Individuals in Small Groups," *The Journal of Psychology: Interdisciplinary and Applied*, vol. 38, no. 1, pp. 139–149, 1954.
- [15] L. C. Freeman, "Centrality in Social Networks: Conceptual Clarification," *Social Networks*, vol. 1, no. 3, pp. 215–239, 1978-1979.
- [16] L. C. Freeman, "A Set of Measures of Centrality Based on Betweenness," *Sociometry*, vol. 40, no. 1, pp. 35–41, 1977.
- [17] S. P. Borgatti and M. G. Everett, "A Graph-theoretic perspective on centrality," *Social Networks*, vol. 28, no. 4, pp. 466–484, 2006.
- [18] S. E. Seibert, M. L. Kraimer, and R. C. Liden, "A Social Capital Theory of Career Success," *The Academy of Management Journal*, vol. 44, no. 2, pp. 219–237, 2001.
- [19] A. Mehra, A. L. Dixon, D. J. Brass, and B. Robertson, "The Social Network Ties of Group Leaders: Implications for Group Performance and Leader Reputation," *Organization Science*, vol. 17, no. 1, pp. 64–79, 2006.
- [20] T. T. Baldwin, M. D. Bedell, and J. L. Johnson, "The Social Fabric of a Team-Based M.B.A. Program: Network Effects on Student Satisfaction and Performance," *The Academy of Management Journal*, vol. 40, no. 6, pp. 1369–1397, 1997.
- [21] R. T. Sparrowe, R. C. Liden, S. J. Wayne, and M. L. Kraimer, "Social Networks and the Performance of Individuals and Groups," *The Academy of Management Journal*, vol. 44, no. 2, pp. 316–325, 2001.
- [22] A. Enders, H. Hungenberg, H.-P. Denker, and S. Mauch, "The long tail of social networking. Revenue models of social networking sites," *European Management Journal*, vol. 26, no. 3, pp. 199–211, 2008.
- [23] N. Gandal, C. I. King, and M. Van Alstyne, "The Social Network within a Management Recruiting Firm: Network Structure and Output," *Review of Network Economics*, vol. 8, no. 4, 2009, article 2.
- [24] S. Zanella and I. Pais, *The Adecco Global Study 2014: Job Search, Digital Reputation and HR Practices in the social media age*. Adecco Group, 2014.
- [25] C. R. Wanberg, R. Kanfer, and J. T. Banas, "Predictors and Outcomes of Networking Intensity Among Unemployed Job Seekers," *Journal of Applied Psychology*, vol. 85, no. 4, pp. 491–503, 2000.
- [26] V. Venkatesh, J. Y. L. Thong, and X. Xu, "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology," *MIS Quarterly*, vol. 36, no. 1, pp. 157–178, 2012.
- [27] J. Donath and d. boyd, "Public Displays of Connection," *BT Technology Journal*, vol. 22, no. 4, pp. 71–82, 2004.
- [28] J. J. McCall, "Economics of information and job search," *Quarterly Journal of Economics*, vol. 84, no. 1, pp. 113–126, 1970.
- [29] A. M. Spence, "Job Market Signaling," *Quarterly Journal of Economics*, vol. 87, no. 3, pp. 355–374, 1973.
- [30] E. A. J. Van Hooff, C. R. Wanberg, and G. van Hove, "Moving beyond job search quantity: Towards a conceptualization and self-regulatory framework of job search quality," *Organizational Psychology Review*, vol. 3, no. 1, pp. 3–40, 2012.
- [31] J. Thatcher, M. Dinger, and J. F. George, "Information Technology Worker Recruitment: An Empirical Examination of Entry-Level IT Job Seekers Labor Market," *Communications of the Association for Information Systems*, vol. 31, pp. 1–34, 2012.
- [32] H. Krasnova, K. Koroleva, and N. F. Veltri,

- “Investigation of the network construction behavior on social networking sites,” in *ICIS '10 Proc.*, 2010, paper 182.
- [33] R. Buettner, “A Framework for Recommender Systems in Online Social Network Recruiting,” in *HICSS-47 Proc.*, 2014, pp. 1415–1424.
- [34] S. Macdonald, “Headhunting in high technology,” *Tech-novation*, vol. 4, no. 3, pp. 233–245, 1986.
- [35] T. Keim, “Extending the Applicability of Recommender Systems: A Multilayer Framework for Matching Human Resources,” in *HICSS 2007 Proceedings*, 2007, p. 169.
- [36] J. Zhang and M. S. Ackerman, “Searching for Expertise in Social Networks: A Simulation of Potential Strategies,” in *Proceedings of the 2005 international ACM SIGGROUP conference on Supporting group work*, ser. GROUP '05. New York, NY, USA: ACM, 2005, pp. 71–80.
- [37] R. Caers and V. Castelyns, “LinkedIn and Facebook in Belgium: The Influences and Biases of Social Network Sites in Recruitment and Selection Procedures,” *Social Science Computer Review*, vol. 29, no. 4, pp. 437–448, 2011.
- [38] P. Kuhn and H. Mansour, “Is Internet Job Search Still Ineffective?” *The Economic Journal*, vol. 124, no. 581, pp. 1213–1233, 2014.
- [39] R. Buettner, “Towards a New Personal Information Technology Acceptance Model: Conceptualization and Empirical Evidence from a Bring Your Own Device Dataset,” in *AMCIS '15 Proc.*, 2015, in press.
- [40] R. Buettner, “Analyzing the Problem of Employee Internal Social Network Site Avoidance: Are Users Resistant due to their Privacy Concerns?” in *HICSS-48 Proc.*, 2015, pp. 1819–1828.
- [41] O. Oechslein, M. Fleischmann, and T. Hess, “An Application of UTAUT2 on Social Recommender Systems: Incorporating Social Information for Performance Expectancy,” in *HICSS-47 Proc.*, 2014, pp. 3297–3306.
- [42] M. M. Plummer and S. R. Hiltz, “Recruitment in Social Networking Sites: A Theoretical Model of Jobseekers’ Intentions,” in *AMCIS '09 Proc.*, 2009, paper 176.
- [43] M. Plummer, S. R. Hiltz, and L. Plotnick, “Predicting Intentions to Apply for Jobs Using Social Networking Sites: An Exploratory Study,” in *HICSS '11 Proc.*, 2011, pp. 1–10.
- [44] F. D. Davis, “Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology,” *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 1989.
- [45] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, “User Acceptance of Information Technology: Toward a Unified View,” *MIS Quarterly*, vol. 27, no. 3, pp. 425–478, 2003.
- [46] T. Tan, Y. Zhang, and A. Kankanhalli, “How online social networks affect my job choice intention: an empirical approach,” in *PACIS '14 Proc.*, 2014, paper 324.
- [47] A. A. Alchian, “Information Costs, Pricing and Resource Unemployment,” *Western Economic Journal*, vol. 7, no. 2, pp. 109–128, June 1969.
- [48] A. A. Alchian and H. Demsetz, “Production, Information Costs, and Economic Organization,” *American Economic Review*, vol. 62, no. 5, pp. 777–795, December 1972.
- [49] G. J. Stigler, “The Economics of Information,” *Journal of Political Economy*, vol. 69, no. 3, pp. 213–225, June 1961.
- [50] F. Brecht and A. Eckhardt, “Employer branding via social network sites - A silver bullet to attract it professionals?” in *ECIS '12 Proc.*, 2012, paper 89.
- [51] H. van der Heijden, “User Acceptance of Hedonic Information Systems,” *MIS Quarterly*, vol. 28, no. 4, pp. 695–704, 2004.
- [52] M. Hassenzahl, “The Effect of Perceived Hedonic Quality on Product Appealingness,” *International Journal of Human Computer Interaction*, vol. 13, no. 4, pp. 481–499, 2001.
- [53] W. B. Dodds, K. B. Monroe, and D. Grewal, “Effects of Price, Brand, and Store Information on Buyers,” *Journal of Marketing Research*, vol. 28, no. 3, pp. 307–319, 1991.
- [54] S. S. Kim, N. K. Malhotra, and S. Narasimhan, “Two Competing Perspectives on Automatic Use: A Theoretical and Empirical Comparison,” *Information Systems Research*, vol. 16, no. 4, pp. 418–432, 2005.
- [55] M. Limayem, S. G. Hirt, and C. M. K. Cheung, “How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance,” *MIS Quarterly*, vol. 31, no. 4, pp. 705–737, 2007.
- [56] J. A. Ouellette and W. Wood, “Habit and Intention in Everyday Life: The Multiple Processes by Which Past Behavior Predicts Future Behavior,” *Psychological Bulletin*, vol. 124, no. 1, pp. 54–74, 1998.
- [57] R. LaRose and M. S. Eastin, “A Social Cognitive Theory of Internet Uses and Gratifications: Toward a New Model of Media Attendance,” *Journal of Broadcasting & Electronic Media*, vol. 48, no. 3, pp. 358–377, 2004.
- [58] C. Hutto and C. Bell, “Social Media Gerontology: Understanding Social Media Usage among a Unique and Expanding Community of Users,” in *HICSS-47 Proc.*, 2014, pp. 1755–1764.
- [59] S. Nikou and H. Bouwman, “The Diffusion of Mobile Social Network Service in China: The Role of Habit and Social Influence,” in *HICSS-46 Proc.*, 2013, pp. 1073–1081.
- [60] A. M. Saks, “Multiple predictors and criteria of job search success,” *Journal of Vocational Behavior*, vol. 68, no. 3, pp. 400–415, 2006.
- [61] R. Kanfer, C. R. Wanberg, and T. M. Kantrowitz, “Job Search and Employment: A Personality-Motivational Analysis and Meta-Analytic Review,” *JAP*, vol. 86, no. 5, pp. 837–855, 2001.
- [62] S. Zhao, “Do Internet Users Have More Social Ties? A Call for Differentiated Analyses of Internet Use,” *Journal of Computer-Mediated Communication*, vol. 11, no. 3, pp. 844–862, 2006.
- [63] R. Kraut, M. Patterson, V. Lundmark, S. Kiesler, T. Mukophadhyay, and W. Scherlis, “Internet paradox: A social technology that reduces social involvement and psychological well-being?” *American Psychologist*, vol. 53, no. 9, pp. 1017–1031, 1998.
- [64] B. Gonçalves, N. Perra, and A. Vespignani, “Modeling Users’ Activity on Twitter Networks: Validation of Dunbar’s Number,” *PLoS ONE*, vol. 6, no. 8, p. e22656, 2011.
- [65] J. P. Robinson and S. Martin, “IT Use and Declining Social Capital? More Cold Water From the General Social Survey (GSS) and the American Time-Use

- Survey (ATUS),” *Social Science Computer Review*, vol. 28, no. 1, pp. 45–63, 2010.
- [66] R. Kraut, S. Kiesler, B. Boneva, J. Cummings, V. Helgeson, and A. Crawford, “Internet Paradox Revisited,” *Journal of Social Issues*, vol. 58, no. 1, pp. 49–74, 2002.
- [67] R. S. Burt, *Structural holes: The social structure of competition*. HUP, 1992.
- [68] M. S. Granovetter, “The Strength of Weak Ties,” *American Journal of Sociology*, vol. 78, no. 6, pp. 1360–1380, 1973.
- [69] S. Rangan, “The Problem of Search and Deliberation in Economic Action: When Social Networks Really Matter,” *Academy of Management Review*, vol. 25, no. 4, pp. 813–828, 2000.
- [70] M. R. Parks and K. Floyd, “Making Friends in Cyberspace,” *Journal of Communication*, vol. 46, no. 1, pp. 80–97, 1996.
- [71] V. Venkatesh and H. Bala, “Technology Acceptance Model 3 and a Research Agenda on Interventions,” *Decision Sciences*, vol. 39, no. 2, pp. 273–315, 2008.
- [72] C. M. Ringle, M. Sarstedt, and D. W. Straub, “Editor’s Comments: A Critical Look at the Use of PLS-SEM in MIS Quarterly,” *MIS Quarterly*, vol. 36, no. 1, pp. iii–xiv, 2012.
- [73] S. Petter, D. Straub, and A. Rai, “Specifying Formative Constructs in Information Systems Research,” *MIS Quarterly*, vol. 31, no. 4, pp. 623–656, 2007.
- [74] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Thousand Oaks: Sage, 2014.
- [75] N. Urbach and F. Ahlemann, “Structural Equation Modeling in Information Systems Research Using Partial Least Squares,” *Journal of Information Technology Theory and Application*, vol. 11, no. 2, pp. 5–40, 2010.
- [76] W. Revelle, “Hierarchical Clustering and the Internal Structure of Tests,” *Multivariate Behavioral Research*, vol. 14, no. 1, pp. 57–74, 1979.
- [77] J. C. Nunnally and I. H. Bernstein, *Psychometric Theory*, 3rd ed. New York: McGraw-Hill, 1994.
- [78] E. G. Carmines and R. A. Zeller, *Reliability and Validity Assessment*. Beverly Hills, CA, USA: Sage, 1979.
- [79] J. F. Hair, C. M. Ringle, and M. Sarstedt, “PLS-SEM: Indeed a Silver Bullet,” *Journal of Marketing Theory & Practice*, vol. 19, no. 2, pp. 139–152, 2011.
- [80] B. Efron and R. J. Tibshirani, *An Introduction to the Bootstrap*. Chapman & Hall, 1993.
- [81] W. W. Chin, *The Partial Least Squares Approach for Structural Equation Modeling*, 1998, In *Modern Methods for Business Research*, Marcoulides, G.A. (ed.), Lawrence Erlbaum Associates, Mahwah, NJ, USA, pp. 295–336.
- [82] C. Fornell and D. F. Larcker, “Evaluating Structural Equation Models with Unobservable Variables and Measurement Error,” *Journal of Marketing Research*, vol. 18, no. 1, pp. 39–50, 1981.
- [83] J. Henseler, C. M. Ringle, and R. R. Sinkovics, *The use of partial least squares path modeling in international marketing*. Emerald, 2009, vol. 20, pp. 277–319.
- [84] S. B. MacKenzie, P. M. Podsakoff, and C. B. Jarvis, “The Problem of Measurement Model Misspecification in Behavioral and Organizational Research and Some Recommended Solutions,” *Journal of Applied Psychology*, vol. 90, no. 4, pp. 710–730, 2005.
- [85] C. M. Ringle, S. Wende, and A. Will. (2005) Smartpls 2.0 (beta). University of Hamburg. <http://www.smartpls.de>.
- [86] S. Geisser, “A Predictive Approach to the Random Effect Model,” *Biometrika*, vol. 61, no. 1, pp. 101–107, 1974.
- [87] M. Stone, “Cross-Validatory Choice and Assessment of Statistical Predictions,” *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 36, no. 2, pp. 111–147, 1974.
- [88] D. X. Peng and F. Lai, “Using partial least squares in operations management research: A practical guideline and summary of past research,” *Journal of Operations Management*, vol. 30, no. 6, pp. 467–480, 2012.
- [89] M. E. Sobel, “Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models,” *Sociological Methodology*, vol. 13, pp. 290–312, 1982.
- [90] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed. Hillsdale, NJ, USA: Lawrence Erlbaum, 1988.
- [91] S. P. Borgatti and D. S. Halgin, “On Network Theory,” *Organization Science*, vol. 22, no. 5, pp. 1168–1181, 2011.
- [92] R. Garg and R. Telang, “Role of Online Social Networks in Job Search by Unemployed Individuals,” in *ICIS ’12 Proc.*, 2012.
- [93] L. Pöbneck, H. Hofmann, and R. Buettner, “Physical Theories of the Evolution of Online Social Networks: A Discussion Impulse,” in *ICIW ’12 Proc.*, 2012, pp. 137–142.
- [94] X. N. Deng and E. H. Chi, “Understanding Postadoptive Behaviors in Information Systems Use: A Longitudinal Analysis of System Use Problems in the Business Intelligence Context,” *Journal of Management Information Systems*, vol. 29, no. 3, pp. 291–326, 2012.
- [95] X. N. Deng and E. J. Davidson, “Knowledge Boundaries and Spanning Practices in Configuring Packaged Systems,” *Journal of Information Technology Case and Application Research*, vol. 15, no. 1, pp. 37–66, 2013.
- [96] X. N. Deng and Y. Liu, “Understanding Knowledge Transfer Dynamics in Information System Support: An Exploratory Study of Procurement System Support,” in *HICSS-46 Proc.*, 2013, pp. 3674–3683.
- [97] X. N. Deng and T. Wang, “Understanding Customer-Oriented Organizational Citizenship Behavior in Information System Support: An Exploratory Study,” in *HICSS-46 Proc.*, 2013, pp. 4115–4124.
- [98] D. Kahneman, P. P. Wakker, and R. Sarin, “Back to Bentham? Explorations of Experienced Utility,” *Quarterly Journal of Economics*, vol. 112, no. 2, pp. 375–406, 1997.