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CROWDSOURCING FOR SURVEY RESEARCH: WHERE AMAZON MECHANICAL TURKS DEVIATES FROM CONVENTIONAL SURVEY METHODS

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Abstract

Information systems research has started to use crowdsourcing platforms such as Amazon Mechanical Turks (MTurk) for scientific research, recently. In particular, MTurk provides a scalable, cheap workforce that can also be used as a pool of potential respondents for online survey research. In light of the increasing use of crowdsourcing platforms for survey research, the authors aim to contribute to the understanding of its appropriate usage. Therefore, they assess if samples drawn from MTurk deviate from those drawn via conventional online surveys (COS) in terms of answers in relation to relevant e-commerce variables and test the data in a nomological network for assessing differences in effects. The authors compare responses from 138 MTurk workers with those of 150 German shoppers recruited via COS. The findings indicate, inter alia, that MTurk workers tend to exhibit more positive word-of mouth, perceived risk, customer orientation and commitment to the focal company. The authors discuss the study's results, point to limitations, and provide avenues for further research.

Keywords: Crowdsourcing, Amazon Mechanical Turks, Survey Research, e-Commerce, Word-of-Mouth

1 Introduction

In recent years, the crowdsourcing phenomenon has attracted much research attention (e.g, Estellés-Arolas and González-Ladrón-de-Guervara 2012, Füller et al. 2012, Majchrzak and Malhotra 2013). Departing from well-known practical real life crowdsourcing phenomena such as InnoCentive (research and development), Threadless (Design) and Amazon Mechanical Turks (scalable workforce), research has started to answer important theoretical and practical questions concerning task owners and task solvers. Thereby, crowdsourcing, defined as "the outsourcing of tasks to a large group of people instead of assigning such tasks to an in-house employee or contractor" (Alonso and Lease 2011, p. 1), has been identified to be used for different types of tasks. For example, firms have used the crowd to generate ideas through ideation contests (e.g., Hutter et al. 2011, Leimeister et al. 2009), to rate and evaluate ideas (e.g., Blohm et al. 2011, Riedl et al. 2013), and to advance ontology databases (e.g., Snow et al. 2008).

Recently, information systems (IS) research has started to use crowdsourcing platforms such as Amazon Mechanical Turks (MTurk) for scientific research (Crowston 2012). In particular, MTurk provides a scalable, cheap workforce that can also be used as a pool of potential respondents for online survey research (Peer et al. 2014). While other disciplines such as political sciences and psychology already have used MTurk to collect survey data, the IS discipline remains rather reluctant (Crowston 2012). However, also (behavioural) IS research might benefit from an increased use of crowdsourcing platforms such as MTurk.

Two commonly expressed concerns of using MTurk include (1) representativeness and (2) quality of data (e.g., Buhrmester et al. 2011). In terms of representativeness, MTurk shares the same advantages and disadvantages as conventional online surveys (COS) (Andrews et al. 2003). For example, MTurk is not representative of a specific region or population. However, studies that aimed to replicate research findings derived from conventional student samples revealed that MTurk leads to comparable results (e.g., Berinsky et al. 2012). In addition, if used correctly, data quality of MTurk data sets may be considered high (Peer et al. 2014).

Thus, in light of the increasing use of crowdsourcing platforms for survey research, we aim to contribute to our understanding of its appropriate usage. In particular, our research aim is twofold. First, we want to assess if samples drawn from MTurk deviate from those drawn via COS in terms of answers in relation to e-commerce (in contrast to prior research that has centred on differences in demographic structures; see Crowston 2012). To reach this aim we compare respondents' answers to questions that focus on well-known and often-used aspects in e-commerce research. These aspects include online shoppers' perceived risk, silent endurance, commitment, customer orientation, and positive and negative word-of-mouth (e.g., Ba and Pavlou 2002, Beatty et al. 2012, Cunningham et al. 2005, Koufaris and Hampton-Sosa 2004, Quereshi et al. 2009, Yoon 2002). Second, we aim to test the data in a nomological network for assessing differences in effects between variables.

The remainder of the article is organized as follows. First, we briefly provide a theoretical underpinning for crowdsourcing in general and give an overview on related work on crowdsourcing for survey research in particular. Second, based on existing literature we propose differences between an MTurk sample and conventionally recruited online samples in how respondents evaluate e-commerce shopping scenarios. Third, based on two datasets of 138 US-based MTurk workers and 150 German shoppers we test our assumption that MTurk workers rate shopping scenarios differently compared to conventional Internet populations. As potential differences might also be attributed to cultural differences, we test for measurement invariance and discuss nations' properties in relation to Hofstede (1983). Finally, we report and discuss our results, point to the limitations of this study, and provide avenues for further research.

2 Related work

2.1 Crowdsourcing as a solution to distant search

Crowdsourcing is heavily related to problem-solving and the problem-solving perspective of the knowledge-based view (Schaarschmidt et al. 2013). Each task that is assigned to the crowd may be viewed as a problem. Sometimes the problem is quite complex and not everyone in the crowd is capable of solving it. Here, those who distribute the task are interested in few good solutions rather than a large amount of solutions. In other cases, the amount of solutions is crucial for successful problem-solving such as in situations where problem-solvers rate pictures in order to establish ontology databases (Snow et al. 2008).

This seemingly diverse problem-space causes various modes of using crowdsourcing for problem-solving. As a response to missing classifications of problems and related crowdsourcing practices, Tripathi et al. (2014) introduced a socio-technical systems perspective on crowdsourcing, which involves five main components. In particular, they distinguish co-creation, crowd-creation, crowd voting, crowd wisdom, and crowd funding. All of them might be viewed as a solution to organizations' distant search (Afuah and Tucci 2012).

In a more theory-driven approach, Afuah and Tucci (2012) argue that the decision to crowdsource a problem is dependent on (1) the characteristics of the problem, (2) the knowledge required for the solution, (3) the crowd, and (4) the solutions to be evaluated. Concerning the first aspect, the researchers distinguish decomposable from non-decomposable problems, of which the latter are less suited for crowdsourcing. Based on this line of reasoning, seeking respondents for a survey shares the characteristics of a decomposable problem. That is, the problem as such is not very complex but the solution to this problem is quite distributed. Thus, using crowdsourcing for survey research, a scenario that corresponds with Tripathi et al.'s (2014) crowd voting, is suitable from a theoretical point of view. However, compared to traditional survey research methods, we lack an understanding of if and how data that is generated via MTurk deviates from COS methods or not.

2.2 Crowdsourcing for survey research

Many scientific disciplines have used crowdsourcing platforms such as MTurk to recruit participants for online survey research. At MTurk, more than 300.000 workers from over 100 countries await so-called Human Interaction Tasks (HIT) (Alonso and Lease 2011). These HITs are designed by requesters who seek solutions to their problems. A HIT that involves filling in an online survey may take minutes or even up to hours. As MTurk workers receive their compensation only if they fully complete the survey (at least this is the common design at MTurk), completion rates are generally high. An average compensation of workers should range between $6 and $10 per hour – depending on tasks' complexity. Thus, a survey that is designed to take about 5 minutes should be compensated with at least $ 0.5.

However, due to comparatively low payment, prior research was concerned about data quality of datasets generated via MTurk (e.g., Buhrmester et al. 2011). On the other hand, only about 12% of US based MTurk workers indicated that MTurk is their primary income (Alonso and Lease 2011) – a fact that points to complementing motives to participate such as fun and avoidance of boredom (Kaufmann et al. 2011). In addition, numerous studies exist that have proven the trustworthiness of MTurk as a method for online survey research. For example, Mason and Suri (2012) report that in repeated surveys, only one out of 207 participants changed the answer on gender. In another study, Peer et al. (2014) investigated how workers react to attention check question based on the reputation they have at MTurk. An indicator for reputation at MTurk is a HIT approval rate of more than 95%, that is, the worker has been approved for his work in more than 95% of his tasks. Peer et al. (2014) found in relation to reliability that high reputable workers rarely failed to answer attention checks correctly. However, there are also studies that report that about 30% of workers do not answer questions properly when no quality selection is done (e.g. Downs et al. 2010, Kaufmann et al. 2011). Based on these and other studies, Crowston (2012) recommends using a mixture of both recruiting high quality workers (e.g., HIT approval rate above 95%) and including attention check question in survey (e.g., "Please answer the following question with 'agree'"). The core of his recommendations is depicted in Table 1.

Research concern	**Data about MTurk workers**
Reliability	Use multiple indicators per construct
Internal validity	Prevent or remove duplicate responses Consider effects of monetary compensation on research questions
Spam	Examine time taken to perform task Include check questions
External validity	Not perfectly representative of Internet users but not worse than alternatives

Table 1. Recommendations to address reliability and validity with MTurk as source for survey research (adapted from Crowston 2012)

In sum, a large amount of research exists that either used MTurk as a means to recruit participants or investigated sampling and data quality of MTurk data sets. However, research that compares MTurk datasets with those collected via COS remains scarce.

3 Proposition

The population on MTurk is not as diverse as previously thought. A 2008-2009 study found that workers are predominantly US based, female, educated, bored – and that money is a secondary incentive compared to others such as fun, avoiding boredom, and socialization (Alonso and Lease 2011). In a similar vein, Ross et al. (2010) report that only 15% of US based MTurk workers earn less than $10.000/year. However, there are slight differences between MTurk workers and standard Internet samples. For example, according to Buhrmester et al. (2011), MTurk participants were more demographically diverse than standard Internet samples.

While differences in samples' demographics are important in terms of representativeness, the core of this study is not to address issues of representativeness but to identify differences in ratings. We surmise that MTurk workers have the tendency to either overrate e-commerce related constructs or perceive issues differently due to their familiarity with Internet-based work. In particular, MTurk workers should perceive shopping scenarios as less risky and tend to exhibit more positive word-of-mouth than conventional Internet samples. We investigate differences in evaluations of shopping scenarios with an experimental design and in relation to often-used concepts in e-commerce research such as perceived risk, silent endurance, commitment, customer orientation, and positive and negative word-of-mouth (e.g., Beatty et al. 2012).

4 Method

4.1 Data Collection and Sample

To investigate differences between answers from a crowd and answers from "conventional" shoppers, we used an online survey and a quasi-experimental research design. We were interested in a series of evaluations of a specific firm as it is common in behavioural information systems and marketing research (e.g., Beatty et al. 2012, Walsh et al. 2009, Yoon 2002). To ground participants' answers in real life experiences, we chose a company that is (1) globally known and (2) has an online business model. Among several companies that would fulfil these requirements, we decided to use eBay.

In a pre-test it turned out that respondents did not fully know if their answers should be related to their role as buyers of products offered at eBay's website or as sellers. For the main study we clarified this issue and asked respondents to answer in relation to their role as buyers. We further surmised that differences in answers could be considerably apparent in an online shopping vs. an offline shopping scenario. As online surveys are also used for evaluating offline shopping scenarios, we included a treated control group that had to answer questions in relation to McDonalds, a company with an offline business model. Thus, our research design mirrors a 2 (eBay; Online shopping vs. McDonalds; Offline shopping) x 2 (MTurk vs. COS) experimental design.

To recruit participants, we first created a HIT on MTurk that involved completing the survey. Participants were recruited via a posting that reads "Answer a short survey on shopping behaviour; takes 5 min at maximum". As a requirement for participation, workers must be US-based citizens and had to have at least a HIT approval rate of 95% on at least 100 tasks (Oppenheimer et al. 2009). We offered a compensation of US$ 0.5 for completed tasks. Average time per assignment was 5:19 min for an effective hourly wage of US$ 5.64. To increase the chance of collecting high-quality data, we followed the suggestion by Peer et al. (2014) and included a series of attention check questions. These involved items such as "Please rate this question as 'agree'". As workers only will receive their compensation after they filled in the entire questionnaire, drop-outs were limited to a few respondents (details below).

After we collected the intended number of MTurk worker responses, we changed the survey language to German. Thus, we used the same online survey in a German version and recruited participants with the help of student research assistants. These assistants were asked to distribute a link to the online survey to friends and family members. Together, both procedures resulted in 406 useable answers of which 148 stem from MTurk and 258 from German shoppers. In total, 66 respondents dropped out early. Further, we had to exclude four cases of respondents who needed less than 2 minutes for the questionnaire, which was considered the minimum time required to capture the scenario as well as the main questions. Twelve responses had to be excluded because respondents did not pass manipulation checks (i.e., recalling the name of the company for which they answered) or attention checks. Finally, we had to exclude 36 responses (only 3 from the MTurk group) because of missing values.

This procedure led to a data set consisting of responses from 138 MTurk workers and 150 German shoppers. Both subsets are comparable as indicated by a similar distribution of male (approx. 60%) and female (approx. 40%) respondents. The majority of respondents have A level degrees or completed their studies. However, both subsets deviate in terms of Job (majority MTurk=employee; majority COS=student) and experience with the studied companies. In particular, MTurk workers indicated to have more experience with eBay than German shoppers – a fact that underlines the Internet-affinity of MTurk workers. The full demographics are depicted in Table 2.

4.2 Measures

We used multi-item measures of the important variables such as perceived risk, positive and negative word of mouth, customer orientation, commitment and silent endurance.[1] These variables relied on existing validated scales and were measured on seven-point Likert scales ranging from 1 = strongly

[1] For reasons of space, we do not report definitions of our variables of interest as it is common in scientific. This paper's focus is on the differences of MTurk and COS samples and only to a lesser degree the relation between constructs as such. Definitions are available upon request.

disagree, to 7 = strongly agree. A bi-lingual speaker translated the items form English to German for the questionnaire. The subjects were randomly assigned to the scenarios (i.e., eBay vs. McDonalds) which required minor adjustments of item wording with regard to the company name.

	MTurk (n = 138)		COS (n = 150)	
	Frequency	Percentage	Frequency	Percentage
Gender				
Male	84	60.87	87	58.00
Female	54	39.13	63	42.00
Age				
< 20	3	2.17	5	3.33
20 – 29	70	50.72	118	78.67
30 – 39	38	27.54	21	14.00
40 – 49	8	5.80	5	3.33
≥ 50	19	13.77	1	0.67
Education				
Lower secondary education	0	0.00	2	1.33
Middle school degree	1	0.73	24	16.00
Technical high school degree	3	2.17	18	12.00
High school degree	50	36.23	55	36.67
College graduate	79	57.25	48	32.00
Other	5	3.62	3	2.00
Job				
Employee	78	56.52	51	34.00
Worker	9	6.52	5	3.33
House Husband / House Wife	5	3.62	0	0.00
Student	11	7.97	69	46.00
Self-Employed	16	11.60	7	4.67
Pensioner	2	1.45	0	0.00
Retiree	0	0.00	1	0.67
Official	0	0.00	9	6.00
Unemployed	13	9.42	1	0.67
Prefer Not to Say	3	2.17	3	2.00
Other	1	0.73	4	2.67
Experience with company				
eBay (Mean)	5.12		4.19	
McDonalds (Mean)	4.74		4.61	

Note: Experience with company is measured on a seven point scale ranging from 1 “very low” to 7 “very high”

Table 2. Demographics

Perceived risk. To consider the multidimensional nature of perceived risk, we took general risk as an assessment that includes various forms of risk (Laroche et al. 2005). This scale measures the degree to which a person views negative consequences concerning the purchase. We measured perceived risk by using the following five items; “There is a good chance I will make a mistake if I purchase from <company>.”; “I have a feeling that purchasing at <company> will really cause me lots of trouble.”;

“If <company> makes a claim or promise about its product, it’s probably true.”; “In my experience, <company> is very reliable.”; “I feel I know what to expect from <company>.”

Positive word of mouth. To operationalize positive word of mouth as a multi-item construct we used the items recommended by Verhoef et al. (2002). These items involve: “I say positive things about <company> to people I know”; “If somebody asks advice with regard to a good <company> of the <industry >, I recommend this one”; “I encourage relatives and friends to do business with <company>”.

Negative word of mouth. We operationalized negative word of mouth by adapting three items suggested by Jones et al. (2007). We asked the subjects to assess the following items from their point of view. “I have warned my friends and relatives not to do business with <company>”, “I have complained to my friends and relatives about this <company>”, and “I have told my friends and relatives not to use products and services of <company>”.

Customer orientation. To assess customer orientation, we used the customer orientation dimension of the multi-dimensional construct of customer-based corporate reputation by Walsh, Beatty and Shiu (2009). This construct includes items such as “The company treats its customers in a fair manner”; “The company’s employees are concerned about customer needs”; “The company’s employees set great store by a courteous customer treatment” “The company takes customer rights seriously”.

Commitment. To measure commitment we asked the subjects about their relation to the company by using the items from Henning-Thurau et al. (2002). “I am very committed to this company.” “My relationship with this company means a lot to me.” “If this company would not exist any longer, it would be a hard loss for me.”

Silent endurance. Silent endurance is measured by adapting the items from Beatty et al. (2012). “I don’t bother to complain to this service provider if I have a problem.” “It is not worth the effort to complain to them.” “I don’t bother to offer suggestions to them.” “It is not worth the effort to offer suggestions for improvements.”

Controls. To control for potential influences on the dependent variables by alternative variables we included a set of controls, such as respondents age, gender, and experience with the focal company.

4.3 Measurement model evaluation

The measurement model was assessed with a confirmatory factor analysis (CFA) using AMOS 21 and a maximum likelihood estimator. As suggested by Kline (2005), the fit indexes for assessing model fit involve chi-square (χ^2), degrees of freedom (*df*), root mean square error of approximation (RMSEA), standardized root mean square residual (SRMR), and comparative fit index (CFI). The 21 items that reflect our multi-item measures (i.e., silent endurance, commitment, risk, positive word of mouth, negative word of mouth, and customer orientation) revealed a good fit with the data, indicated by χ^2 = 374.64, df = 170, p = .000 and χ^2/df = 2.204 (Byrne 1989). The CFA also yielded a good fit regarding RMSEA of .06 with a 90% confidence interval ranging from .055 to .073, which did not exceed the suggested cut-off value of .08 for a reasonable well fitting. Finally, the results show a SRMR-value of 0.56 and an acceptable CFI of .95. All together, the fit indices support the choice of our measurement.
In a second step, we aimed to ensure discriminant and convergent validity of the measurement model. Construct reliability (computed with composite reliability) exceeds the recommended threshold of 0.7 for all constructs of interest. In addition, the average variance extracted (AVE) for all constructs is greater than 0.5. Finally, to ensure discriminant validity, the square root of AVE should be greater than inter-construct correlations, a demand that is fulfilled by the data (Bagozzi and Yi 2012; Fornell and Larcker 1981). Detailed information on measurement and correlations between constructs is provided in Table 3.

	CR	AVE	SE	COM	PR	PWOM	NWOM	CO
SE	0.82	0.54	**0.73**					
COM	0.89	0.74	-0.37	**0.86**				
PR	0.86	0.60	0.34	-0.20	**0.77**			
PWOM	0.89	0.73	-0.45	0.82	-0.36	**0.86**		
NWOM	0.90	0.75	0.46	-0.25	0.60	-0.39	**0.86**	
CO	0.87	0.63	-0.49	0.62	-0.27	0.69	-0.45	**0.80**

Notes: The diagonal displays the square root of AVE. SE=Silent Endurance, COM=Commitment; PR=Perceid Risk; PWOM=Positive Word-of-Mouth; NWOM=Negative Word-of-Mouth; CO=Customer Orientation

Table 3. Convergent validity, discriminant validity and correlations

4.4 Invariance tests

As we compared American MTurk workers with German shoppers, we had to test for possible measurement invariance. Previous studies showed that some of our variables are robust against cultural differences (e.g., customer orientation as part of the customer-based corporate reputation construct; Walsh et al. 2009). However, prior research has revealed that MTurk workers who have a low reputation (i.e., below 90% HIT approval rate) provide lower quality answers in terms of factor reliability (Peer et al. 2014). Hence, we compared both data sets for similar patterns of factor loadings (configural invariance, i.e., both groups associate the same subsets of items with the same constructs) and for equality of factor loadings (metric invariance, i.e., all factor loading parameters are equal across groups) (Walsh et al. 2009).

Measurement difference might be attributed to sample size (Brannick 1995). We have 138 MTurk workers and 150 German online shoppers which might be considered equivalent in terms of sample size. To test for configural invariance, we used an unconstrained model in AMOS reflecting our variables of interest (comparable to CFA). Both subsets revealed a comparable pattern of factor loadings. In addition, we tested for metric invariance as this is especially useful for exploring nomological relationships. This test involves constraining factor loadings to be equal across the groups (Steenkamp and Baumgartner 1998). Again, this test supports our assumption that both measures are equivalent.

4.5 Test of common method bias

We used the same methods and procedures for all our measured variables. This potentially poses the threat of common method variance (CMV; Podsakoff and Organ 1986). CMV is less of a concern in experimental studies where only dependent variables are actually measured. However, our second aim with this study is to investigate the influence of being an MTurk worker on positive and negative word-of-mouth in a nomological network. To be able to make such predictions we have to ensure that CMV is not an issue in this study.

We used two of several possible tests for estimating CMV. First, we used Harman’s single factor test which is based on the assumption that in the case of CMV one construct should explain the majority of the variance in reflective items. We conducted a factor analysis in SPSS without rotation and found that a single factor reflecting our 21 items only accounts for 37% of the variance. This result suggests that the data is not affected by CMV because the variance accounted for is well below the threshold of 50%. Second, we used the measured latent factor approach suggested by Lindell and Whitney (2001). A three-item measure of social desirability (α=.65), which is theoretically unrelated to our model variables, was used as the marker variable. We ran a CFA in AMOS with and without the marker variable. If CMV is present, factor loadings for the model variables (i.e., silent endurance, perceived risk, customer orientation, positive and negative word of mouth, commitment) in a model with marker variable deviate substantially from a model without the marker variable. The highest difference in factor loadings we found was .08 for RISK_2, which is why CMV may be considered not present for this study.

4.6 Testing of assumptions

We were able to compare answers from 150 German shoppers recruited via COS methods with answers from 138 MTurk workers. 70 German shoppers answered in relation to eBay and 80 in relation to McDonalds. Of the 138 MTurk workers, 69 voted in relation to eBay while 69 voted in relation to McDonalds. To assess differences in answering behaviour, we used a MANOVA implemented in SPSS 21. The advantage of a MANOVA in comparison to a series of ANOVAs is the potential reduction of type-I-errors (Cohen 2013). We modelled survey type (MTurk vs. COS) and company (eBay vs. McDonalds) as independent variables and silent endurance, perceived risk, customer orientation, positive and negative word-of-mouth, and commitment as dependent variables (Table 4).

		MTurk vs. COS						
		MTurk		COS		*F*		
Variable	*Scenario*	*M*	*SD*	*M*	*SD*	*S*	*A*	*S×A*
Silent endurance	eBay	3.25	1.39	3.56	1.38	25.74***	7.22	0.02
	McDonalds	4.17	1.71	4.49	1.63			
Perceived risk	eBay	3.01	1.36	2.87	1.27	0.00	9.29**	3.48
	McDonalds	3.24	1.24	2.66	1.61			
Customer orientation	eBay	4.71	1.24	4.45	0.78	11.29**	5.68*	0.20
	McDonalds	4.32	1.19	3.95	1.14			
Positive WOM	eBay	4.60	1.56	3.62	1.43	33.53***	22.04***	0.74
	McDonalds	3.43	1.65	2.70	1.48			
Negative WOM	eBay	2.14	1.41	1.95	1.11	31.24***	1.73	0.06
	McDonalds	3.17	1.71	2.89	1.66			
Commitment	eBay	3.32	1.82	2.25	1.21	13.75***	26.01***	1.52
	McDonalds	2.48	1.47	1.83	1.71			

Notes: M=Mean, SD=standard deviation, MTurk =Sample drawn from Amazon Mechanical Turks, COS=Sample recruited via conventional online survey, S=Difference between shopping scenarios, A=Difference between MTurk group and COS group, *p<.05, **p<.01, ***p<.001

Table 4. Mean Values of Shopping Scenarios and Results of MANOVA

Regarding the data collection methods (i.e. MTurk vs. COS), we found no difference in ratings concerning silent endurance, and negative word-of-mouth. However, perceived risk ($F_{1,287} = 9.29$, $p < .01$, $\eta^2 = .02$), customer orientation ($F_{1,287} = 5.68$, $p < .05$, $\eta^2 = .02$), positive word-of-mouth ($F_{1,287} = 22.04$, $p < .001$, $\eta^2 = .07$), and commitment ($F_{1,287} = 26.01$, $p < .001$, $\eta^2 = .08$) show significant differences in relation to the data collection method. In particular, MTurk workers generally perceive the shopping contexts as more risky, which is surprising. The results indicate that MTurk workers might be more sensitive towards risk in Internet shopping than conventional shoppers. Perceive customer orientation in companies as higher, display more positive word-of-mouth and are more committed to the company than German shoppers. With regard to the difference between online and offline contexts (i.e. eBay vs. McDonalds), votings in relation to eBay are more positive in nature than votings for McDonalds. This mirrors the results of a pretest we conducted with 30 German respondents who had to evaluate four globally known firms in terms of their reputation (Walsh and Beatty 2007). Here, respondents evaluated McDonalds as less reputable in comparison to eBay on five reputation-related dimensions. Although we would have liked to have online and offline contexts with identical reputation to exclude reputation bias, we took eBay and McDonalds despite their deviating reputation as this difference was lower than the difference with the other pair (Apple vs. Ford). In particular, respondents perceive less silent endurance in relation to eBay compared to McDonalds, rate customer orientation and commitment at eBay as higher, and do less negative and more positive word-of-mouth in relation to eBay. The results yielded no difference in terms of perceived risk.

In sum, the results reflect a rather low reputation of McDonalds compared to eBay. However, as none of the interaction effects yielded significance, the difference between answers from MTurk workers and German online shoppers are not caused by the online (eBay) vs offline (McDonalds) context. Thus, the difference between MTurk and COS may entirely attributed to the different type of data collection.

While the results show that there are differences in how people that were recruited via COS and MTurk workers evaluate shopping contexts, this says nothing about how this difference affects relationships between variables. For example, in marketing and e-commerce research, word-of-mouth is usually seen as an outcome of commitment and a firm's customer orientation (Henning-Thurau et al. 2004). Thus, to investigate the effect the survey method has on a relation's strength, we put our variables in a proven nomological network (Walsh et al. 2009). Based on prior research, we treat positive and negative word-of-mouth as two distinct dependent variables (Beatty et al. 2012). Commitment, customer orientation, perceived risk, and silent endurance are treated as independent variables. We used the entire data set of 288 responses and regressed positive and negative word-of-mouth on these independent variables, controls (i.e., gender, age) and the type of data collection (1=MTurk, 0=COS).

	Model 1 PWOM	Model 2 NWOM
Independent variables		
Commitment	.49***	.04
Customer orientation	.26***	-.27***
Perceived risk	-.16***	.41***
Silent endurance	-.11**	.21***
Controls		
Gender	-.09*	.06
Age	-.01	-.00
Variable of interest		
MTurk (1=MTurk, 0=COS)	.10*	.06
R^2	.65	.40
F	74.02***	26.52***
N	288	288

Note: MTurk=Sample drawn from Amazon Mechanical Turks, COS=Sample recruited via conventional online survey

Table 5. OLS Regression with MTurk group as independent variable

As depicted in Table 5, commitment (β=.49, $p<.001$) and customer orientation (β=.26, $p<.001$) are significantly related to positive word of mouth. Perceived risk (β=-.16, $p<.001$) and silent endurance (β=-.11, $p<.01$) have a negative effect on positive word-of-mouth. These results map well with what has been shown in prior research (e.g., Beatty et al. 2012). However, the fact that participants were recruited via MTurk has also a significant effect on positive-word-of mouth (β=.10, $p<.05$). This indicates that MTurk workers are more prone to do positive word-of-mouth than their conventionally recruited counterparts.

Concerning negative word-of-mouth, the results are also in line with the pertinent theory. As shown in prior studies, commitment has no effect of negative word-of-mouth (β=.04, n.s.). Customer orientation has a negative effect (β=-.27, $p<.001$) while perceived risk (β=.41, $p<.001$) and silent endurance (β=.21, $p<.001$) have a positive effect on negative word-of-mouth. Interestingly, the difference in survey type has no effect on the dependent variable.

5 Discussion

5.1 Summary of findings and implications for research

We join the conversation on crowdsourcing platforms as useful means to collect survey data. Our results of surveying MTurk workers and German shoppers replicate prior findings in terms of data quality. In particular, reliability and validity of MTurk data may be considered good as indicated by multiple indicators (see 4.3). Moreover, as the invariance tests show, data quality of the MTurk data set does not deviate from the German data set, which is in line with prior studies (e.g., Peer et al. 2014).

In this study, we were not only interested in possible differences in data quality but in how MTurk workers rate e-commerce related firm attributes. We compared responses from MTurk workers with those of German shoppers recruited via COS on a bunch of e-commerce related variables. Results indicate that MTurk workers tend to exhibit more positive word-of mouth, perceived risk, customer orientation and commitment to the focal company. The results yielded no differences concerning silent endurance and negative word-of-mouth.

In behavioural survey research that is concerned with relations and causality, the rating as such is less of importance than the strength of relations between variables. Therefore, we integrated our measures in a nomological network to see if results for the MTurk data set are comparable to prior research. We found that all paths from independent to dependent variables (i.e. positive and negative word-of-mouth) are in the anticipated direction and level of significance. However, we found that being MTurk worker also significantly explains positive word-of-mouth. Thus, overall variance explained may be little higher than in comparable Internet samples.

Our results add to the current understanding of using crowdsourcing for survey research. As previous research has outlined, MTurk especially is suitable to conduct survey research if Internet users are the intended population. We extend current knowledge by showing that MTurk workers tend to overrate some e-commerce related variables and that being MTurk worker as such has a positive influence on positive word-of-mouth. Future research that uses MTurk data should take these findings into account.

5.2 Limitations and further research

As with any research, ours is not free of limitations. First, we used randomly chosen constructs that are intensely used in e-commerce research. However, this selection was not based on a conceptual framework. Future research might investigate other important variables in IS research. Second, we aimed at investigating differences between online and offline shopping scenarios. We used globally known companies for both scenarios (i.e. eBay and McDonalds) which differ in their reputation. Having two scenarios of similar reputation would have been better but as none of the interaction effects was significant, this concern is of minor importance.

Finally, our biggest limitation pertains to the difference between US based MTurk workers and German shoppers recruited via COS. That is, the differences between survey methods could be also attributed to cultural differences. Future research could replicate our findings by using a suitable sample of US based Internet users. However, to shed more light on our results we briefly discuss cultural differences between Germany and US. Hofstede (1983) maintains that nations differ across six dimensions, namely power distance, masculinity, pragmatism, individualism, indulgence and uncertainty avoidance. According to Hofstede[2], power distance and masculinity are almost equal between Germany and US. However, pragmatism is higher in Germany (G: 83; US: 26) and individualism is lower (G: 67, US: 91). Still, Germany is considered individualistic too in some studies. Indulgence is higher in US (G: 40; US: 68). Finally, Germany has a slight tendency for uncertainty avoidance compared to US (G: 65; US: 46). In sum, although there are difference between Germany and US, (1) the differences are not as large as for other pairs of countries and (2) except for uncertainty avoidance which might be connected to perceived risk, the dimensions have little theoretical connection to the variables of interest for this study. Thus, although cultural differences exist, they are less likely to affect this study's results.

[2] URL: http://geert-hofstede.com/germany.html, last access: October 2014.

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