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ABSTRACT

Multiple facets of factors were examined to be drivers for crowdsourcing intention.However,there is limited research that has studied whether this factors-intention link is uniform for all solvers or not in detail.In fact,the present studies have identified three different segments that are internally consistent and stable. The comparison between the results of two different solutions, single-class and prediction-oriented-segmentation, confirms the existence of unobserved solver segments. The three established segments are "Self-leading solvers", "External-driving solvers" and "Dual-driving solvers". These results point the way for factors-based segmentation in intention initiatives and reflect the importance of a multidimensional conceptualization of factors, comprising motivation, perceived sponsor's and platform's support components.The paper expands and deepens the application of the heterogeneity theory in the study of crowdsourcing usage behavior and offers implications for organizers to recognize the solvers more clearly and get directions for more valid strategies.

Keywords: Crowdsourcing, Solvers, Participation Intention, Heterogeneity Theory.

INTRODUCTION

Growing businesses face a large set of problems, such as improving the innovation performance while at the same time reducing the costs, using the collective intelligence effectively.To overcome these challenges, opening up their innovation activities to crowds has been viewed as a genuine opportunity for companies. With the development of internet and the improvement of consumers' capacity to acquire knowledge, this solution becomes a reality. Recently, a new model for problem solving, defined by Jeff Howe as crowdsourcing[22], has gained substantial interest in the practice and literature.

The vast majority of research on crowdsourcing hasfound that groups areremarkably intelligent and often smarter than the smartest people in them[33].Page [28]points that theproblem benefits by having a number of individuals from cognitively diverseperspectives offering their solutions, even if those individuals are not themselvesexperts.Accordingly, in order to continue applying the crowdsourcing model, a coherent set of conditions for makinga successful crowdsourcing arrangement is needed.This involves understanding the factors that influence the crowd to participate in these creative problem-solving activities. With someexisting research findings begin to explain the factors that induce high level of intention to participate in crowdsourcing[2][26] [29][34][36][42],however,only a few studies have explicitly accounted for the role of heterogeneity in the cognition of solvers on the importance of these factors. Additionally, an aggregate analysis of factors and its relation to intention may result in misleading parameter estimates and target-lacked strategies.

Against this background, the present study examines the factors contributing to high intention from the angles of solvers, sponsor and platform through a series of online questionnaire surveys. Furthermore, this study adds examinations on unobserved heterogeneity regarding the factors-intention linkfor the purpose of solver segmentation, a needed supplement to the existing quantitative portrait on crowdsourcing. The segments we identify differ regarding their perceived important factors and associated effects on intention towards the crowdsourcing participation.

The present study will be beneficial to scholars and managers.Factors summarized from the integration of three perspectives bring implications for future research. The application of heterogeneity theory in the area of crowdsourcing expands a new insight into the intriguing landscape of existing data on factors in crowdsourcing generally. Knowledge regarding different solver groups willhelp crowdsourcing organizers tailor more targeted and effectiveincentives. Furthermore, determining which factors drive high intention will be helpful for organizers to develop solvers attraction programs. This study also contributes to the study of unobserved heterogeneity, which is still an under-research area.

CONCEPTUALBACKGROUNDANDMODELDEVELOPMENT

In this section, the theoretical framework that guides the empirical study is discussed. The literature on solver heterogeneity and the practicability of segmentation based on the factors-intention link and the empirical methods adopted for this research are introduced in detail.

Prior Literature On Solver Heterogeneity

The conception of heterogeneity has drawna substantial of attentionin the area of consumer behavior. Smith [30]is the first author who has pointed the importance of market segmentation. He madean assumption that a heterogeneous market wasconsisted of a number of smaller homogeneous markets with different preferences. Since its introduction, the heterogeneity has become a hot concept in both marketing theory and practice. Many works have discussed the segmentation based on various factors, focusing on the demographic characteristics as well as life-style, personality and usage information[17]. However, the work of segmentation based on these obvious variables would be easy to understand and determine, but might not provide the best explanatory power. As a consequence, many scholars realized the need to recognize the role of heterogeneity on the customer perceptions and expectations in order to develop firm strategies [13]. Similarly, Blasco, Velazquez and Saura [5]estimatedthe effect of customer heterogeneity on the relationship satisfaction-loyalty and obtainedthe result that there had beenthree latent segments where the strength of causal relationships differed. They pointedthat there wasan overestimation of the impact of customer satisfaction on loyalty and the enterprises might fall into the trap of satisfaction if heterogeneity were ignored. Floh et al. [17]used the finite mixture analysis based on the perceived value-loyalty intentions link and recognized three classes of customers: rationalists, value maximizers and functionalists. They pointed that perceived value influencedbehavioral intentions, but the effects differed in magnitude depending on the consumer segment.

In the application of crowdsourcing,the heterogeneity of solvershas also been recognized.Boudreau and Lakhani [6] discussed the best form of crowdsourcing for a given situation and pointed that a well-functioning crowd wasloose, decentralized and varied in skills, experience and perspectives. In the opinion of Brabham [8], diversity of crowd in gender, sexuality, race, nationality, economic class, etc.wereimportant because these unique identities shaped their worldview. Crowd wasbetter at producing differing superior solutions because the ideas might consider the unique needs of diverseconstituencies. Lakhani and Wolf [25]usedthe k-means cluster analysis to figure outwhether there wereany natural groupings of individuals by motivation type. They identifieda four-cluster solution with the best balance of cluster size, motivational aggregation, stability and consistency. They madea clear conclusion that the F/OSS community hadheterogeneous in motives to participate and contribute.

In general, extant researches account forthe solvers' heterogeneity from the perspective of demographic information and motivation. There is limited research that has considered the effect of influencing factors on participation intention. In other words,prior work has identified solver segments based on motivation factors while the effectof aboveand other factors have been neglected.

The Influencing Factors-Participation Intention Link

Participation intention

Intention is used to express how much effort an individual is willing to exert in order to perform the intended behavior[1]. In the context of crowdsourcing, the "participation intention"is defined as 'the behavior intention of a solver who expects to participate in the crowdsourcing activities and the subjective probability of solver's exposure to the problem-solving situation'[27]. Factors affecting the participation intention can be summarized from the angle of process. According to Howe [22]and Brabham [9], the process of crowdsourcing starts from companies operating problems or challenges to the crowd based on broadcasting. Individuals in the crowd offer solutions to these problems. In the end, while the individual providing the winning solution is rewarded some form of a bounty, often in cash, the companies take these ideas into exploitation and sometimes profit by selling finished products back to the crowd. For solvers, contacting aspects involved in the process are the developer itself, the task and platform. So, except for solvers' motivation, the sponsor and platform can also be drivers.

Extrinsic motivation and intrinsic motivation

Drawing upon the works of Deci, Koestner and Ryan [12] and Zheng, Li and Hou [41], extrinsic motivation wasdefined as the motivation to work for something apart from and external to the work itself, such as reward or recognition from other people. Intrinsic motivation indicated the motivation to participate an activity for its inherent satisfactions rather than for some separable consequences. When intrinsically motivated, people would act for fun or challenges entailed rather than pursuing external prods,pressures or rewards[12]. In early studies, solvers' motivation research focused on the area of open source software projects. Sub dimensions included user need, enjoyment, reputation, developing skills, the love of community, reciprocity, sense of efficacy, vocational development, altruism, etc.[24][25][27].

In the area of crowdsourcing, current research results on motivation give more attentionson external interests.Brabham [8]indicatedthat the desire to make money, to develop individual skills, and to have fun werethe strongest motivations for participation at iStockphoto. Another research in Threadlessshowedthat the solvers weremotivated by the opportunity to make money, the opportunity to develop one's skills,the potential to take up freelance work, and the love of community at Threadless[7]. Feng and Huang [16] used the grounded theory method to summarize the solvers' motivation of crowdsourcing. They foundthat solvers' motivation couldbe divided into intrinsic, extrinsic, and internalized extrinsic motivation and they weremutually reinforcing each other.

Taken together, this discussion suggests that factors in perspective of solvers lie in motivation, including extrinsic and intrinsic motivation. The extrinsic motivation couldbe explained in two dimensions: external stimulus and personal interests. The two sub dimensions for intrinsic motivation are enjoyment, sense of achievement.This literature and research findings are summarized in the following hypotheses.

Hypothesis 1 (H1). A solver's extrinsic motivation is positively driven by external stimulus (H11) and personal interests (H12), and it has an positive significant effect on the participation intention (H13).
Hypothesis 2 (H2). A solver's intrinsic motivation is positively driven by enjoyment (H21) and sense of achievement (H22), and it has a positive significant effect on the participation intention (H23).

Factors in respect of sponsor

Researches generally recognize that factors in respect of sponsor can be accounted by two dimensions:task design and sponsor's reputation.

Various explanations suggested to account for the effect of task design on participation have beenmade by Füller [15]and Zwass [43]. Boudreau and Lakhani [6] indicated that a proper description of problem, appealing prizes and opportunities, a well-prepared scoring system, explicit terms and technical specifications wereessential to promote a contest in crowdsourcing. Zheng, Li and Hou [41] suggested that contest autonomy, variety, and analyzability were positively associated with intrinsic motivation, whereas contest tacitness was negatively associated with intrinsic motivation. They foundthat crowdsourcing contest tasks should preferably be highly autonomous, explicitly specified, and less complex, as well as requiringa variety of skills. Shao et al. [29] argued that higher awards, easier tasks,longer duration and lower competition intensity led to a higher number of solvers. Higher awards, longer duration and higher difficulty level of tasks attributedto higher ability level of winners.In the work of Chandler and Kapelner [10],it was found that the more meaningfullya task had been framed, the more likely to participate the workers been.

Previous studies on sponsor's reputation have shown that the nature of sponsor is of importance to intention and solvers are more willing to trust corporate sponsor[40]. Jones and Leonard [23]suggested that third party recognition hadan effect on individual's trust in C2C e-commerce. Similarly, sponsor wouldincrease the security sense and enhance participation intention of solvers by providing the authentication information through the platform[29][42]. Xu and Wang [38]foundthat the enterprise sponsor who providedadequate authentication informationcould attract a higher number of solvers. Ahigher sponsor's credit rating and more seasonable payment led to a higher number of solvers as well as higher ability level of solvers. Additionally, a good image of sponsor can also be an important driver of intention[31].

All these ideas willbe summarized in the following hypothesis.

Hypothesis 3 (H3). Perceived sponsor's support is positively driven by task design(H31) and sponsor's reputation(H32), and it has a positive significant effect on the participation intention (H33).

Factors in respect of platform

As defined by Geiger, Rosemann and Fielt [19], platform referred to information systemsthat assimilated human and computational agents tofacilitate the process of outsourcing a task andaggregating ideas from the crowd. In principle, functions embedded in the web-based platform couldbring the solvers additional value. Furthermore, for crowdsourcing platform to support these salient functions, a good condition of resources support and website experience have to be in place[19][35].

In the light of Doan, Ramakrishnan and Halevy [14], a good condition of resources support couldenhance the capacity of a platform to attract participants, including having an evaluation system to monitor the quality and credibility of the contributions, assuring compensation or reward to the contributors, and maintaining a balance between openness and privacy. Additionally, various examinations have revealed the positive relationship between platform's support and the performance of solvers. Gong, Guo and Fang [20], for example, indicated that the huge amount of available tasks neededa task recommendation system for solvers to find the "right" task to accomplish. Sun et al. [32]showed that the platform environments, reflected by reliability, creativeness, communication mechanism, study behavior among solvers and recommendation, wereimportant drivers to the successful rate of solvers.

Further, the website experience can directly affect the efficiency of completion process. The system's quality, embodied in the web design, operation convenience, platform stability and the validity of the link, plays an important role in participation intention [37]. In addition, the high level of platform's usability can lead to a higher degree of participation[35].

Thus, conditions of platform may influence individual's intention to be a solver. The following hypotheses summarize this argument.

Hypothesis 4 (H4). Perceived platform's support is positively driven by conditions of environmental resources (H41) and website experience (H42), and it has a positive significant effect on the participation intention (H43).

Model Development

Figure.1 shows the conceptual model for this study. The model reveals the above mentioned factors-intention link and helps exploring the moderating role of unobserved heterogeneity in enhancing participation of sponsors and solvers in the crowdsourcing task. This framework integrates research issues at the intersection of work motivation, task seeking and web-based system characteristics. The focus of this research is recognizing the role of heterogeneity in the solvers' cognition of the factors' importance.

Underlying the conceptual framework, four two-order latent variables are established, measured by two one-order latent variables respectively. Except for the participation intention, all the latent constructs are measured in a formative way. This can be justified by examining typical items used in this study.

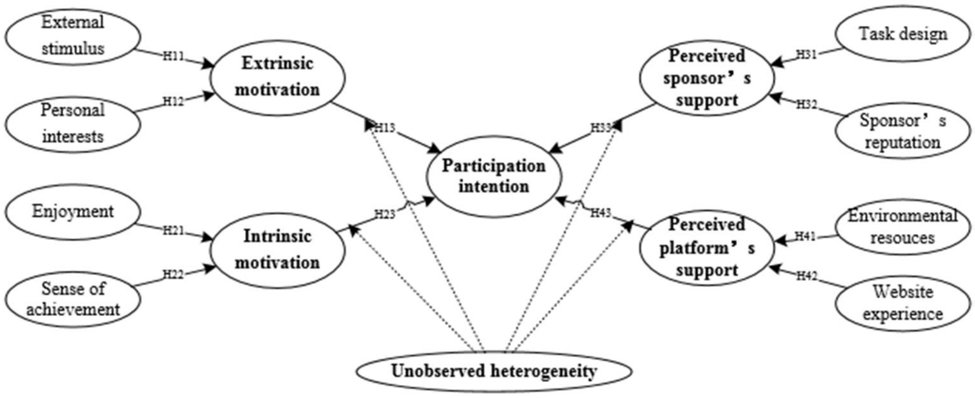

Figure 1: Conceptual model of participation intention in crowdsourcing

METHODOLOGY

Data Collection And Sampling

We test the model shown in Fig.1 by designing a study that consistsof three rounds of investigation. Firstly,we check the face validity of the scales that are adapted from prior validated instruments by inviting many crowdsourcing scholars and managers to discuss and resolve the inconsistency and ambiguities in the formulation.

Secondly, we publish a preliminary survey with a small number of people regardless of their crowdsourcing experience to detect misunderstandings of the items. Subsequently,162 solvers complete the survey. Based on the pre-survey data, we conduct an exploratory factor analysis with SPSS 19.0 to evaluate the effectiveness of the individual items. Principle component analysis reveals that the model with four two-order variables is better than the onewith eight one-order variables. The factor loadings on the intended constructs all are well above 0.575, with no cross-loadings higher than 0.5. The exploratory factor analysis reveals a simple factor structure for this study. The data confirms the multidimensional conceptualization of factors.

Thirdly, a formal online survey is conducted among thepeoplewho have attended at least one task at the Witmart(http://www.witmart.com/). Witmart is a crowdsourcing contest platform in China whichwas founded in 2006. By September 1, 2016, there have been10 million registered solvers and 5 million sponsors. This platform created a 7 billion transaction amount and occupied 80% of the market share in 2015. On this typical platform, we published a task to conduct the survey. In the demand description part, we indicated that the nature of the task wasa research project that aimedto explain the difference of solvers' cognition. Participants in the task wouldget the reward after we have givena pass to their certification of filling in questionnaire. A total of 252 persons participated in the survey. Since only fully completed questionnaires with more than 3 minutes filling time are considered to be valuable in our analysis, the final dataset comprises 239 observations.Sample statistics are shown in Table.1. We can get the features of these participants: young, highly-educated and highly-earned.

Table 1: Sample statistics

Characteristics	Frequency	Percentage	Characteristics	Frequency	Percentage
Gender			Education		
Male	117	49%	High school	33	14%
Female	122	51%	2-3 years of college	67	28%
			4 years of college	126	53%
Age			Graduate school	13	5%
≦18	1	0%	Income(RMB)		
19-25	84	35%	≦1000	33	14%
26-35	137	57%	1001-3000	62	26%
36-45	17	7%	3001-5000	74	31%
≧46	0	0	≧5001	70	29%

Path Model Estimation AndResults Assessment

We choose the PLS approach to model estimation because its formal premise embody a greater range of flexible applications[21]. Furthermore, the aim of our research is to determine the effect of formative latent factors. Accordingly, the PLS approach is more suitable in this regard. However, since the lack of good-of-fit measures in PLS path modeling, a catalogue of non-parametric criteria is needed to assess partial model structures. At first, model assessment focus on the measurement models and only if the computed latent variable scores show evidence of sufficient reliability and validity is it worth pursuing the evaluation of inner path model estimates[21]. In accordance with the steps in PLS path model evaluation from outer model to inner model, we use the SMARTPLS3.0 to the following results.

Assessment of the reflective measurement model

Criteria for reflective measures are composite reliability(over 0.7)[3], factor loadings and average variance extracted (AVE over 0.5). Additionally, for any latent variable, the square root of AVE should be higher than its correlation with any other latent variable[18]. Results show that all factor loadings lie well above the suggested threshold value of 0.7. With a value of 0.745, theAVE is highly satisfactory. The highest correlation value is 0.762, which is lower than the square root of AVE value 0.863. Composite reliability is at 0.921. Accordingly, a high level of reliability exists in our reflective measurement model. Taken together, all the requirements for the reflective measurement model for the endogenous latent variable "participation intention" have been achieved.

Assessment of the formative measurement model

In a well-fitting formative measurement model, all the measurement path loadings should be significant. In addition, the convergent validity should be assessed by creating a reflective factor parallel to the formative factor and the formative factor should be correlated and be able to predict values of the reflective factor[11]. Table.2 shows that all path loadings in the exogenous latent variable's measurement models are significant [$p<0.01$, two-side test; the results are obtained by applying a bootstrapping procedure]. All the path coefficients between the eight formative factors and theirs corresponding reflective ones are at 1.00, passing the standard of 0.9. Hence, all the formative measurement models have satisfactory reliability and validity. We also need to check if the level of multi-collinearity is a critical issue. In the formative measurement models, the highest variance inflation factor (VIF) has a value of 2.951, lower than the threshold 4.0. As a consequence, the multi-collinearity does not pose a problem in this study.

Table2: Significance of path loadings

Path	T-value	path	T-value
ES1→External stimulus	15.516	TD1→Task design	13.679
ES2→External stimulus	7.559	TD2→Task design	10.105
ES3→External stimulus	7.231	TD3→Task design	7.058
ES4→External stimulus	14.538	TD4→Task design	7.253
ES5→External stimulus	15.26	TD5→Task design	6.733
PI1→Personal interests	14.061	TD6→Task design	6.803
PI2→Personal interests	16.684	TD7→Task design	10.26
PI3→Personal interests	11.625	SR1→Sponsor's reputation	2.748
EN1→Enjoyment	11.393	SR2→Sponsor's reputation	3.442
EN2→Enjoyment	16.478	SR3→Sponsor's reputation	12.218
EN3→Enjoyment	17.684	SR4→Sponsor's reputation	9.738
SA1→Sense of achievement	19.514	SR5→Sponsor's reputation	20.876
SA2→Sense of achievement	15.359		
SA3→Sense of achievement	6.886	ER1→Environmental resources	16.859
SA4→Sense of achievement	11.818	ER2→Environmental resources	17.01
WE1→Website experience	18.6	ER3→Environmental resources	16.844
WE2→Website experience	16.43	ER4→Environmental resources	21.886
WE3→Website experience	14.966	ER5→Environmental resources	21.745
WE4→Website experience	21.194	ER6→Environmental resources	13.002

Hypotheses testing: the structural model

All the hypotheses are tested in PLS with the software SMARTPLS 3.0. The central criterion for the assessment of structural model is the coefficient of determinationR^2. With a value of 0.681,the$R^2$of the endogenous latent variable "participation intention" lies at a very satisfactory level, which means that our research model explains 68.1 percent of the variance in participation intention. As shown in Table.3, External stimulus and personal interests have significant effect on extrinsic motivation.Therefore, H11 and H12 are supported. On the other hand, extrinsic motivation is significantly associated with participation intention, which explains H13. Furthermore, H21 and H22 can be confirmed for that we find that both enjoyment and sense of achievement are important drivers of intrinsic motivation. However, H23 is not verifiedbecause the intrinsic motivation has no influence on participation intention. The antecedent factors of perceived sponsor's support and perceived platform's support are found to be positively related, which highly prove H31, H32, H41, and H42. Both the perceived sponsor's support and perceived sponsor's support exert positive effect on participation intention, which verifyH33 and H43.

The process of verifying relevant assessment criteria in respect of the PLS approach concludes at this point. Our analysis suggests that all measures used are reliable and valid and the path from intrinsic motivation to participation intention should be deleted. Consequently, we get the correct model (shown in Fig.2)and some implications to explain and increase the participation intention of solvers can be derived from the analysis results.

Table 3: Hypotheses testing

Path	Coefficient	T-value	Hypotheses	Significance level
External stimulus→Extrinsic motivation	0.657	21.995	H11	p<0.001
Personal interests→Extrinsic motivation	0.444	14.374	H12	p<0.001
Extrinsic motivation→Participation intention	0.184	2.347	H13	p<0.1
Enjoyment→Intrinsic motivation	0.531	17.766	H21	p<0.001
Sense of achievement→Intrinsic motivation	0.576	19.938	H22	p<0.001
Intrinsic motivation→Participation intention	0.001	0.016	H23	not significant
Task design→Perceived sponsor's support	0.649	28.017	H31	p<0.001
Sponsor's reputation→Perceived sponsor's support	0.468	17.216	H32	p<0.001
Perceived sponsor's support→Participation intention	0.147	1.733	H33	p<0.1
Environmental resources→Perceived platform's support	0.551	22.842	H41	p<0.001
Website experience→Perceived platform's support	0.516	19.873	H42	p<0.001
Perceived platform's support→Participation intention	0.566	7.176	H43	p<0.001

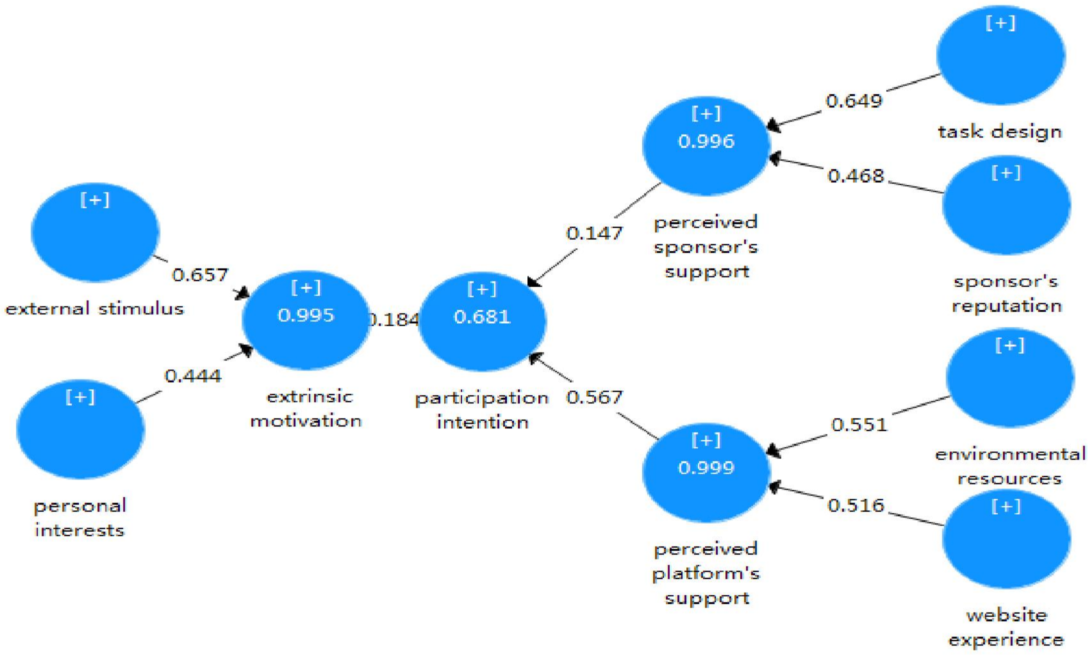

Figure 2: Correct model of participation intention in crowdsourcing

Groups RecognizingBased On Prediction-Oriented-Segmentation

Model estimation

To examine the role of heterogeneity, we selected a prediction-oriented segmentation method. Researches show that the technique is superior to PLS-TPM and REBUS-PLS since (1)an explicit PLS-specific objective criterion has been used to form homogeneous groups; (2) it includes a new distance measure that is appropriate for PLS path model with both reflective and formative measures and is able to uncover unobserved heterogeneity in formative measures; (3) it ensures continuous improvement of the objective criterion throughout the iterations of the algorithm (hill-climbing approach)[4].

Technically speaking, prediction-oriented segmentation method is on the basis of a distance measure, which can identify proper observations to form homogeneous groups. Within a group, there is a norm: the shorter the distance of observationito group g, the higher the predictivity of observationiin group g. Firstly, we should calculate the conceptual difference between observation i's membership in its current group k ($k = g; k, g \in G$)and its distance to an alternative group g ($k \neq g; k, g \in G$). For each endogenous latent variable b($b \in B$), the group-specific prediction of the endogenous latent variable scores ($\hat{Y}_{big}$) through linear combinations between the latent variable scores of its direct predecessors ($Y_{a_b ik}^{exogenous}$) with the corresponding structural model path coefficients ($P_{a_b g}$) is calculated, as shownin Equation 1.

$$\hat{Y}_{big} = \sum_{a_b=1}^{A_b} Y_{a_b ik}^{exogenous} \times P_{a_b g} \qquad (1)$$

Secondly, the difference between the predicted value $\hat{Y}_{big}$ and the current group's latent variable scores Y_{bik} is expressed in Equation 2.

$$e_{big}^2 = (\hat{Y}_{big} - Y_{bik})^2 = (\sum_{a_b=1}^{A_b} Y_{a_b ik}^{exogenous} \times P_{a_b g} - Y_{bik}^{endogenous})^2 \tag{2}$$

Thirdly, we can get the new prediction-oriented PLS-POS distance measure by Equation 3.

$$D_{kig} = \sum_{b=1}^{B} \sqrt{\frac{e_{big}^2}{\sum_{i=1}^{I_k} e_{big}^2}} \tag{3}$$

The smaller the value of D_{kig}, the higher the predictivity of observationiin group g. However, calculating the group-specific residual term in models with formative measures requires an extension of the group-specific residual e_{big}^2 in the distance measure, shown in Equation 4. The $x_{a_b jik}$ value ofderives from the manifest variable scores and $\pi_{a_b jg}$ demonstrates the corresponding measurement model's formative weights.

$$e_{big}^2 = (\sum_{a_b=1}^{A_b} \sum_{j}^{J} x_{a_b jik} \times \pi_{a_b jg} \times P_{a_b g} - Y_{bik}^{endogenous})^2 \tag{4}$$

Determining the number of groups

Based on the PLS-POS method and correct model, we carry out a series of POS models with K=2, 3 segments (we have calculated model solutions with more than 3 groups, but topped since the group size became too small to calculate), to explore the number of groups and group probabilities.

According to Becker et al. [4], the aim of PLS-POS is to maximize the sum of the endogenous latent variable's R^2 values. Table.4 shows the R^2 values for each solution. We select the model with K=3 as the final solution for the following reasons: first, the Average Weighted R^2 clearly favors a three-group solution. Second, with the increase of the value of K, most of the R^2 values of each segment presents positive trend.

Table 4: Comparison of R^2 for models with k=2,3 groups

Constructs	**Original Sample R^2**	**K=2**		
		Average Weighted R^2	**POS Segment 1**	**POS Segment 2**
Participation intention	0.681	0.76	0.707	0.941
Extrinsic motivation	0.995	0.993	0.996	0.991
Perceived sponsor's support	0.996	0.997	0.996	0.998
Perceived platform's support	0.999	1	1	1
Constructs	**K=3**			
	Average Weighted R^2	**POS Segment 1**	**POS Segment 2**	**POS Segment 3**
Participation intention	0.874	0.862	0.857	0.955
Extrinsic motivation	0.995	0.994	0.997	0.992
Perceived sponsor's support	0.996	0.996	0.996	0.998
Perceived platform's support	1	1	1	1

Results

Based on the K=3 solution and the estimation of each segmentwe get the path coefficients results and sample statistics for each segment on the basis of final partition information, presented in Table.5. As a consequence, we find that solvers are heterogeneous and there are three groups of them. In the overall model, three critical direct predictors of participation intention are all shown to be important drivers. However, in the three POS models, the three main coefficients are in stark contrast. Path coefficient value of extrinsic motivation to participation intention is positively significant in group 1 and 3, conversely, negatively related in group 2. Similarly, group 1 and 2 both suggest that the perceived sponsor's support positively associated with participation intention but group 3 shows a different result. Furthermore, perceived platform's support have a strong effect on participation intention in group 2 and 3 but not significantly associated in group 1. These differences also show effect on the explained variance. The R^2 of classes 2 and 3 are significantly higher than that of the single-class solution. In addition, these differences verify the assumption that a homogeneous sample does not hold when measuring the link between factors and participation intention in crowdsourcing.

Table 5: Multi-group results

Path (coefficients)	**Group 1**	**Group 2**	**Group 3**

External stimulus→Extrinsic motivation	0.7***	0.596***	0.68***
Personal interests→Extrinsic motivation	0.418***	0.465***	0.43***
Extrinsic motivation→Participation intention	0.675***	-0.295***	0.793***
Task design→Perceived sponsor's support	0.626***	0.564***	0.602***
Sponsor's reputation→Perceived sponsor's support	0.494***	0.516***	0.452***
Perceived sponsor's support→Participation intention	0.209***	0.411***	-0.276***
Environmental resources→Perceived platform's support	0.639***	0.629***	0.664***
Website experience→Perceived platform's support	0.415***	0.449***	0.411***
Perceived platform's support→Participation intention	0.134	0.74***	0.591***

Characteristics		**Group 1（97）**		**Group 2（107）**		**Group 3（35）**	
Gender		Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
	Male	48	49%	50	47%	19	54%
	Female	49	51%	57	53%	16	46%
Age							
	≦18	1	1%	0	0	0	0
	19-25	35	36%	37	35%	12	34%
	26-35	56	58%	58	54%	23	66%
	36-45	5	5%	12	11%	0	0
	≧46	0	0	0	0	0	0
Education							
	High school	8	8%	20	19%	5	20%
	2-3 years of college	30	31%	28	26%	9	36%
	4 years of college	56	58%	51	48%	19	54%
	Graduate school	3	3%	8	7%	2	--
Income(Monthly consumption for students)(RMB)							
	≦1000	17	18%	14	13%	2	6%
	1001-3000	18	19%	28	26%	16	46%
	3001-5000	36	37%	29	27%	9	26%
	≧5001	26	27%	36	34%	8	23%

DISCUSSION

Drawing upon an emerging research interest in participation behavior of crowdsourcing (e.g.Shao et al. [29];Terwiesch and Xu [34]), we have established and examined a research model that tests the factors influencing a solver's participation intention. In addition, we investigate the effect of heterogeneity on the relationship factors-intention and summarize three segments for solvers.

Factors influencing solvers' intention embrace three critical components: extrinsic motivation, perceived sponsor's support and perceived platform's support, consistent with previous studies (e.g., Li and Wang [26]; Wang [36]; Xu and Wang [38]). Furthermore, perceived platform's support is found to have a strongest effect and has an obvious dominant characteristic-regardless of the heterogeneity. The intrinsic motivation is not significantly associated with participation intention. Although this finding contradicts several studies (e.g. Boudreau and Lakhani [6];Zheng and Hou [40];Zheng, Li and Hou [41]), we can give some reasonable explanations, gained from later interviews with some solvers. The platform we proposed for data collection questionnaire survey is Witmart. Most of the tasks in Witmart belong to bidding types and the direct result of bid-winning is to get a sum of money. Consequently, solvers are willing to be the member for receiving the bounty when they finish specific tasks, not challenge or a sense of accomplishment and so on.

At the same time, the effect of heterogeneity on the factors-intention link has been verified by identifying the following three groups:

Group 1-Self-leading solvers
Respondents ingroup 1 give substantially highest weight to extrinsic motivation, and, therefore, are called self-leading solvers. To gain a high willingness to participate crowdsourcing fromthis group, the fitness between the participation and their own motivation is of predominant importance. In terms of demographic characteristics, they are the youngest and are evenly divided by gender. Most of them have a bachelor degree and belong to middle income class. In summary, the self-leading solvers are stepping into the initial stage of the struggle for life after the undergraduate studies. The reasons for them to be solvers in crowdsourcing are to improve the utilization value of spare time, to flourish personal skills, to learn new knowledge

and to look for new stimulus outside formal work. Activities organized by sponsor and platform have a low attraction to this group. This type of solvers is one of main forces to accede to crowdsourcing participants.

Group 2-External-driving solvers
For members in group 2, in contrast, perceived support of sponsor and platform are both relevant in forming participation intention towards the crowdsourcing task. Hence, members of this class are called external-driving solvers. However, the extrinsic motivation is shown to be negatively related to the participation intention. For this group, the high intention is induced by recommendation of sponsor's and the sense of community or addiction to a brand of a platform. As far as population information, they are women dominated, older, educated and highly-earnedwhen compared to other groups. In summary, external-driving solvers are mature, experienced, rational, skilled and belonging to the higher level of education and income group. The most important reason to participate is to expand the knowledge base and to capture the modern fresh elements. This group represents the largest class in the analysis.

Group 3-Dual-driving solvers
Members in this group concentrate on the extrinsic motivation and perceived platform's support when evaluating the participation intentions towards crowdsourcing, and, therefore, are called the dual-driving solvers.But conversely, perceived sponsor's support is of no influence. This group is more responsive to their own demands and the attraction established by platform. Bothinside and outside factors work. They are men dominated and most of them are 26-35 years old. They are experienced, but have a lower level of education and income. In the process, they know more about practices than theories on crowdsourcing.They focus on those tasks that are within their own means to enhance the utilization of spare time and gaina small extra income. These solvers are not the main crowd.

All these differences indicate that the cognition of solvers is of great difference. Assuming a homogeneous sample may provide a misleading view of solvers. Managers should recognize the segments of solvers more clearly and establish more valid strategies.

CONCLUSIONS

Implications ForResearch

The present study contributes to the literature in several ways. First, this study is one of the first studies considering the heterogeneity of solvers. Previous studies examine the factors-intention link based on the homogeneous assumption, using a model with regression coefficients reflecting merely the 'midpoints' of given factors(e.g.Shao et al. [29]; Zheng and Hou [40]). Our study, however, summarizes specific cognitive and demographic differences among three sub groups. More importantly, the application of heterogeneity reveals some important implications for future crowdsourcing research.

Second, the current study is also one of the first to recognize the dominant player in the crowdsourcing market. Based on the summary of crowdsourcing process, we suggest that except for the motivation of solvers, the sponsor and platform also have effect on solvers' participation intention. Using the exploratory factor analysis, we find eight one-order influencing factors and theirs corresponding two-order variables. The dimensions we examined can pay some useful reference for future researches.

Implications For Practice

The findings of the present study can also highlight some crowdsourcing design elements for organizers. First, the platform is the dominate player of the three in the crowdsourcing market. For companies, a proper platform with high level of popularity and brand attractiveness is an important move to gain sufficient human resources.

Second, solvers are heterogeneous. Companies should deliver targeted signals according to the type of solvers and task characteristics. If there are middle level requirements of skills for a task but financial support is limited, the self-leading solvers are the optimal choice. In the process, organizers should pay attention to pass these signals, including competitive bounty, high level of credit, and flow experience of website and so on. If there are high level requirements of skills and the financial support is adequate, the extrinsic-driving solvers should be attracted. The important signals that should be delivered including utilization of spare time, good image of sponsor, completeness and robustness of the website's basic functions and so on. If tasks are simple but need collective labors based on limited costs, the dual-driving solvers are the ones they need. In the process, organizers should emphasize on utilization of spare time, transparent rules, good reputation and so on.

Limitations And Outlook

Although this study has strengths, some limitations exist here. First, the variable"participation intention" is measured by solvers' perceptions, which can not be treated as equal to the individual's actual participation. Future research may collect objective data about individual's participation and extend the model in the present study to explore the effect of these influencing factors on participation intention and actual participation. Second, the study does not model or empirically test mediating variables, such as trust, satisfaction and so on, which stillprovides some insights for further studies. Third and finally, to be able to extend the subjects investigated beyond the context of our nation, future research on crowdsourcing is needed. Future studies should comprise subjects with various nationalities and cultural background in order to gain a deeper and more comprehensive understanding of the participate behavior in crowdsourcing.

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