# Inspiring crowdsourcing communities to create novel solutions: competition design and the mediating role of trust

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## Abstract

Online communities have become an important source for knowledge and new ideas. However, little is known about how to create a compelling virtual experience to inspire individuals to make novel contributions. This examination is crucial as participants' time and attention have become increasingly scarce resources in an ever more crowded online space. Drawing from the motivation through job design theory, we develop and test a research framework to examine how motivation can be influenced or triggered by competition design characteristics to drive creativity in crowdsourcing communities. Specifically, we investigate the importance of task and knowledge design dimensions in eliciting levels of motivation leading to creative efforts. Additionally, we consider the mediating influence of trust in driving knowledge contribution behaviour. Our hypothesising suggests that trust in the hosting platform reduces uncertainty and fosters knowledge exchange. Based on an empirical study of Kaggle's data scientists community, it reveals that intrinsic motivation exerts a strong effect on participation intention, which in turn positively impacts participant's creative efforts. Highly autonomous competitions with special emphasis on problem solving that require solvers to perform a variety of tasks will further challenge contestants to apply their abilities and skills leading to greater enjoyment and sense of competence. Our findings provide important implications for Web platform managers for the successful management of crowdsourcing communities.



**Keywords:** crowdsourcing, creativity, trust, motivation, competition design, contributed effort.

## 1. Introduction

Online innovation contests represent a new form of inbound open innovation (Huizingh, 2011) where individuals or institutions take an idea or solution seeking process, traditionally performed by internal employees, and outsource it to an undefined, generally large group of individuals, referred to as the 'crowd', using advanced collaborative technologies (Estellés-Arolas and Gonzalez-Ladron-de-Guerva, 2012, Saxton et al., 2013, Majchrzak and Malhotra, 2013). A growing body of literature has acknowledged the application of online communities for innovation, particularly with regard to exploration and ideation projects (Bayus, 2013, Morgan and Wang, 2010, Parmentier and Mangematin, 2014). These web-enabled systems gather ideas from a crowd of users with diverse skills sets, knowledge and expertise that organisations exploit for the development of novel ideas and solutions (Howe, 2006, Howe, 2008, Surowiecki, 2005). Recognising the capability of crowdsourcing for mobilising the creative efforts of large numbers of individuals, organisations such as IBM are using crowdsourcing to empower employees in collaborative innovation processes (Bjelland and Wood, 2008). Organisations benefit from the collective efforts of individual intelligences and creative synergies that emerge from the interactions among a diverse group of individuals, which lead to higher quality exploratory outputs (Hargadon, 2003, Majchrzak et al., 2004). Further, by inviting a large number of solvers to participate, companies can complete the innovation tasks faster (Morgan and Wang, 2010). Crowdsourcing can help companies to quickly brainstorm new development opportunities that might fall outside the companies' operations and routines. This enables companies to shorten innovation life cycles and enhance corporate competitive advantage by increasing the speed to market of new products and services (Chesbrough, 2003). Crowdsourcing research further suggests that solving innovation tasks via crowdsourcing is cheaper than solving them internally (e.g., Howe, 2008). Although some compensation is required for rewarding solvers, Brabham (2008) study shows that the cost of crowdsourcing is lower than solving the tasks internally in most cases.

The business potential of crowdsourcing as a channel of innovation for companies has urged both management scholars and practitioners to consider how online communities can be sustained and nurtured to generate novel ideas and solutions (Poetz and Schreier, 2012). Crowdsourcing relies on a self-selection process among solvers willing and able to respond to the broadcast innovation contests (Lakhani et al., 2007). However, participants' time and attention have become increasingly scarce resources as the online space grows more crowded with more options for participants to choose from on where and how to spend their time (Wang et al., 2013). Yet, sustained participation is crucial; thus, understanding the specifics of participants' voluntary behaviour to share and create innovation knowledge is central to the design and maintenance of viable crowdsourcing communities (Chiu et al., 2006, Ardichvili et al., 2003).

This paper examines the effect of crowdsourcing competition design in motivation as determinant of participants' creativity in online communities. We draw from the motivation through job design theory (Hackman and Oldham, 1980) to develop and test a theoretical framework that explores the impact of task and knowledge design characteristics in a participation architecture that promotes creativity and innovation. Additionally, we consider the mediating influence of trust in the platform provider in driving knowledge contribution behaviour in knowledge communities. We carry out this investigation in the context of prediction competitions given their potential to address the increasing problems faced by companies in trying to deal with "Big Data" (Manyika et al., 2011). Crowdsourcing allows greater experimentation, enabling organisations to extract value from a gradually more turbulent, unstructured digital data environment (Boudreau and Lakhani, 2013, Garcia Martinez and Walton, 2014).

Our study contributes to community innovation research in two important ways. First, we respond to calls for a better understanding of the triggers of a compelling and enjoyable virtual co-creation experience and their positive effects on creativity (Prahalad and Ramaswamy, 2003, Nambisan and Nambisan, 2008). Crowdsourcing research demonstrates that competition design characteristics can ignite a sense of enthusiasm in participants and propel them to their peak levels of creativity (Huang et al., 2010). Hence, we aim to identify the task and knowledge properties that affect contributed effort in prediction competitions. Second, we expand knowledge in crowdsourcing communities by applying theories of trust to explain the emergence of trust in this environment and its importance to knowledge exchange. Departing from existing research on trust development among community members (Baruch and Lin, 2012, Antikainen et al., 2010), this paper looks at system trust and its mediating influence in cooperative knowledge exchange. Similarly to the selection of design attributes, trust in the hosting platform can influence knowledge sharing (Leimeister et al., 2005).

The paper proceeds as follows. Following the introduction, in section two we draw from the relevant literature on psychology and job design to develop our theoretical model and research hypotheses. In a next step, we discuss our data and measures before empirically investigating the proposed relationships using a variance-based structural equation model (SEM) approach to simultaneously assess these proposed relationships. Finally, we discuss our results and present theoretical and practical implications, and a future research agenda, which takes into account the study's limitations.

## 2. Theoretical framework and hypotheses

### 2.1. Motivational Competition Design Characteristics

Crowdsourcing research presents an extensive coverage of the motivational factors and reward schemes leveraging crowd creative potentials (Fuller, 2006, Fuller, 2010, Frey et al., 2011, Roberts et al., 2006). In contrast, there is still a lack of studies that empirically analyse the competition design attributes that trigger creative efforts while providing participants with a virtual co-creation experience that would attract them to the crowdsourcing platform in the future (Piller and Walcher, 2006). Jobs possess certain characteristics that have psychological implications on individuals' willingness to personally engage in work roles (Foss et al., 2009). Hackman and Lawler (1971) argued that a substantial portion of the variation in worker performance (i.e., internal motivation) could be explained by the characteristics or specific attributes constituting the job and how workers perceived these attributes.

Drawing from motivation through job design theory (Hackman and Oldham, 1980), we consider motivational job characteristics with the potential to elicit motivation in virtual communities. The premise of the motivational approach is that crowdsourcing competitions will be more motivating and satisfying if high levels of tasks and knowledge characteristics are present (Morgeson and Humphrey, 2006). To the extent that participants perceive that these competition design characteristics offer clear and desired benefits for their personal investment, they ought to exhibit an increasing willingness to fully engage in crowdsourcing competitions. In addition to job characteristics that reflect the task, in this paper we also consider knowledge requirements of work (Campion and McClelland, 1993), considered in the creativity literature as critical for creativity (Amabile et al., 1996). Distinguishing between task and knowledge characteristics acknowledge the fact that crowdsourcing competitions can be designed or redesigned to increase task demands, knowledge demands or both to enhance the crowdsourcing experience (Campion and McClelland, 1993). We specifically focus on the impact of two crowdsourcing task dimensions: autonomy and task variety, and three knowledge dimensions: complexity, problem solving and specialisation.

#### *2.1.1. Crowdsourcing task dimensions*

*Task autonomy* is a central work characteristic in motivational work design approaches (Campion, 1988, Hackman and Oldham, 1976). Autonomy refers to the degree of freedom that is allowed to the worker during task execution (Hackman and Oldham, 1980). If more own decisions and creativity are permitted, the worker's motivation will increase (Fuller, 2010, Hackman and Oldham, 1980, Morgeson and Humphrey, 2006). In the context of crowdsourcing communities, if a competition task is not specifically dependent on the sponsor's other jobs and/or business processes, the competition itself has a higher level of autonomy, which in turn offers the solver a higher level of control over his/her actions during the competition (Zheng et al., 2011). If an individual has a high level of control over his/her behaviour, a higher level of intrinsic motivation might emerge. Predictive modelling competitions offer solvers autonomy to highly elaborate in terms of their chosen methodologies, contributing to the creation of scientific insight (Bentzien et al., 2013). We therefore hypothesise that:

***H1: Competition autonomy is positively associated with intrinsic motivation***

*Task variety* refers to 'the degree to which a job requires employees to perform a wide range of tasks on the job' (Morgeson and Humphrey, 2006, p.1323). Jobs that involve the performance of different work activities are likely to be more interesting and enjoyable to undertake (Sims et al., 1976). Thus, a higher level of task variety is likely to encourage solvers to develop solutions from different perspectives (Howe, 2008). If predictive modelling competitions require data scientists to perform different tasks, players might feel more intellectually challenged in applying their analytical abilities and skills to develop novel solutions. Players might also experience increased enjoyment in developing a code or algorithm to the competition. Hence, we hypothesise:

***H2: Task variety is positively associated with intrinsic motivation.***

#### *2.1.2. Crowdsourcing knowledge dimensions*

*Task complexity* refers to 'the extent to which the tasks on a job are complex and difficult to perform' (Morgeson and Humphrey, 2006, p. 1323). The literature suggests a curvilinear relationship between complexity and intrinsic motivation (Wood, 1986). Initially, complexity might have a positive impact on intrinsic motivation because an increasing level of complexity leads to increasing levels of challenge and activation (Morgeson and Humphrey, 2006). When a task is more complex, completing the task can reflect a higher competence; hence it is more likely to satisfy people's needs for competence (Deci and Ryan, 1985). However, later on in the problem-solving process, a high level of complexity places higher cognitive demands to generate unique ideas and solutions (Morgeson and Humphrey, 2006). Therefore, the individual might lose interest and enjoyment in performing the task as he/she is failing to gain a sense of competence (Deci and Ryan, 1985). A recent study by Sun et al. (2012) on sustained participation in online communities however found no difference between low and medium complexity suggesting a stable effect until task complexity reaches a threshold value, beyond which higher complexity will weaken the impact of intrinsic motivation on sustained participation.

In the context of predictive modelling competitions, given the nature of the crowd (i.e., data scientists with specialised knowledge about task activities), we posit that task complexity positively impacts intrinsic motivation. Because predictive modelling competitions involve complex tasks requiring the use of high-level skills and are more mentally demanding and challenging, they are likely to have positive motivational outcomes.

***H3: Competition complexity is positively associated with intrinsic motivation.***

*Problem solving* involves generating unique or innovative ideas or solutions, diagnosing and solving non-routine problems, and preventing or recovering from errors (Jackson et al., 1993, Wall et al., 1990). As with complexity, we expect problem solving to have a positive impact on intrinsic motivation as the quest for new codes and algorithms helps data scientists to gain a sense of competence and self-expression (Shah and Kruglanski, 2000, Lakhani and Wolf, 2003).

***H4: Problem solving is positively associated with intrinsic motivation.***

*Specialisation* refers to 'the extent to which a job involves performing specialised tasks or possessing specialised knowledge and skill' (Morgeson and Humphrey, 2006, p. 1324). Specialisation reflects a depth of knowledge and skill in a particular knowledge domain. To perform well and add value to seekers, solvers in knowledge communities are typically required to have specialised skills or knowledge to undertake competition tasks. For instance, the high task specificity of predictive modelling competitions requires specific domains, and thereby mainly attracts contributors with the necessary knowledge and skills (Zwass, 2010). This in turn motivates solvers to participate in crowdsourcing competitions as a means to further challenge their abilities and gain peer reputation (Leimeister et al., 2009).

***H5: Specialisation is positively associated with intrinsic motivation.***

## 2.2. Intrinsic Motivation in Crowdsourcing Participation Intention

Previous studies have suggested that the major source of intrinsic motivation in crowdsourcing competitions is the sheer fun, enjoyment and satisfaction of developing innovative solutions to challenging problems (Franke and Shah, 2003, Fuller, 2006, Ridings and Gefen, 2004, von Hippel and von Krogh, 2003). Also engaging in social interactions with like-minded peers (Fuller et al., 2006, Kosonen et al., 2014) and recognition by peers (Boons et al., 2015) or by the sponsoring company (Jeppesen and Fredericksen, 2006) have been found to be important motivations.

Organisational psychology literature suggests that tasks that are intrinsically motivating exhibit a direct and strong association between the task and the individual's purpose for performing the task (Calder and Staw, 1975). For data scientists, participating in predictive modelling competitions is an activity they enjoy and serves to test the robustness of their algorithms and theories and to attain a sense of self-worth and achievement by sharing knowledge more openly and effectively with peers (Garcia Martinez and Walton, 2014). Trying to contribute to the creative discovery of solutions seems to be a source of positive feelings of competence, autonomy and self-expression (Shah and Kruglanski, 2000, Lakhani and Wolf, 2003). Thus, individuals who are intrinsically motivated to perform some activity will perform it very intensively. Several studies have shown that intrinsic rather than extrinsic motivations have strong effects in explaining participation efforts and performance of online communities (Zheng et al., 2011, Frey et al., 2011, Sauermann and Cohen, 2010), consistent with the notion of self-determination theory (Deci and Ryan, 1985). Individuals who perceive their own behaviour as largely self-determined are more intrinsically motivated and show longer persistence in their behaviour than individuals with a low perception of self-determination (Vallerand and Bissonnette, 1992, Zuckerman et al., 1978). Howe (2008, p.15) argues that 'people typically contribute to crowdsourcing projects for little or no money, labouring tirelessly despite the absence of financial rewards'. Thus, the following hypothesis is proposed:

***H6: Participants' intrinsic motivation is positively associated with their behavioural intention to participate in crowdsourcing competitions***

### 2.3. Participation Intention and Knowledge Contribution Effort

Behavioural intention has long been regarded as a crucial antecedent of actual behaviour in many technology adoption models, such as the Theory of Planned Behaviour (TPB) (Ajzen, 1991). The TPB model contends that an individual actual behaviour can be predicted by the intention to perform the behaviour. The relationship between intention and behaviour is based on the assumption that human beings attempt to make rational decisions based on the information available to them. Thus, a person's behavioural intention to perform (or not to perform) a behaviour is the immediate determinant of that person's actual behaviour (Ajzen and Fishbein, 1980). Thus, the more a person intends to carry out the intended behaviour, the more likely he or she would do so (Armitage and Conner, 1999).

Based on the TPB, we contend that participants with positive attitudes towards knowledge sharing will exhibit increased contributed efforts. According to Gagné (2009), 'when people feel competent, autonomous and related to others with whom they have opportunities to share knowledge' (p.575), they will be willing to share more. Thus, the following hypotheses are proposed:

***H7: Participants' behavioural intention to participate is positively related to the quality of their submissions.***

***H8: Participants' behavioural intention to participate is positively related to the number of competitions they enter.***

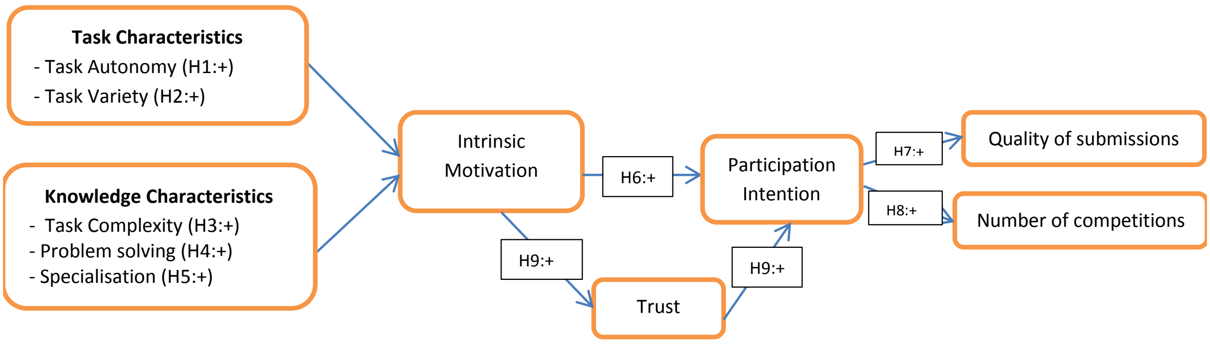
### 2.4. The Mediating Role of Trust

Trust has been recognised as being 'at the heart of knowledge exchange' (Davenport and Prusak, 1998, p.35) and 'the gateway for successful relationships' (Wilson and Jantrania, 1993, p.5). In online communities, trust among participants is critical to the exchange of knowledge and expertise (Hsu et al., 2007, Fang and Chiu, 2010, Decker et al., 2011). Because participation in online communities can be anonymous, participants want to share their knowledge with the expectation that it will be used appropriately. However, few studies have considered system trust in crowdsourcing communities, that is, the interaction between the hosting platform and community members and its impact in knowledge sharing (Leimeister et al., 2005). Crowdsourcing platforms, such as Kaggle and InnoCentive, act as virtual knowledge brokers between the sponsor and the solvers. According to Feller et al. (2012), these brokers 'offer value-added services that mobilised knowledge by helping organisations specify their innovation problems in a manner that will increase the possibility of it being solved by the Virtual Innovation Community' (p. 231). When crowdsourcing via a knowledge broker, solvers interact with the platform host's staff to receive information/feedback, rather than directly with the crowdsourcing sponsor. Thus, we propose that that the host-solver interaction can affect knowledge sharing behaviour.

***H9: Participants' trust in the host mediates the interaction between intrinsic motivation and participation intention.***

Our hypothesised model is depicted in Figure 1.

**Figure 1. Research Framework**




## 3. Methodology

### *3.1. Data and sample*

The empirical setting of this paper is Kaggle (www.kaggle.com), the world's leading online platform for predictive modelling competitions. We use a unique dataset that combines archival data on Kaggle's members contributed efforts with responses to an online survey to capture participants' motivation for participating in prediction competitions. Combining observed data from Kaggle with survey based data allows us to perform a robust test of our model while sidestepping the common method bias concerns of exclusively using survey-based or behavioural data (Podsakoff et al., 2003).

*Survey instrument*

The questionnaire administration and fieldwork took place between April and June 2012. We were given access to 1,700 potential respondents based on the following criteria: (i) respondents had “opted in” to be contacted by Kaggle for marketing and research purposes; and (ii) respondents had achieved a ranking by submitting a minimum of one solution during the tenure of their membership. Potential respondents were then excluded during the survey based on their willingness to provide identifying membership details that would allow us to model their answers alongside actual participation and performance data. An email explaining the aims of the study and containing a link to the web-based questionnaire was sent by Kaggle to selected crowd solvers. Subsequent reminders were published via newsletters and twitter messages. We received data from 293 identified respondents; thereby yielding a response rate of 17%, which compares favourably with other studies on online communities (Zheng et al., 2011, Sun et al., 2012). The analysis was conducted on a total of 222 responses after missing variables were removed. An analysis of non-response bias comparing early responses and late responses regarding research variables and demographic variables revealed no significant differences between the early and the late respondents.

*Performance Data*

For the dependent variables (solvers’ performance in crowdsourcing competitions), we used archival data on respondents’ contributed efforts.

*3.2. Measures*

Measurement items used to operationalise the research constructs were mainly adapted from previous relevant studies (see Appendix A). Slight wording modifications were necessary to make them suitable for the research context with most measures using a seven-point Likert scale with responses ranging from ‘strongly disagree’ (1) to ‘strongly agree’ (7).

*3.2.1. Competition design characteristics*

Consistent with the notion of self-determination theory (Ryan and Deci, 2000b), a goal is only internalised when it is both understood and the individual has the necessary ability or competence to achieve it. The success of crowdsourcing competitions is dependent on the competition design (Leimeister et al., 2009). Pedersen et al. (2013, p.7) argue that ‘a positive user experience is a strong predictor of continued involvement’ of solvers in crowdsourcing competitions. We drew from the Word Design Questionnaire (WDQ) (Morgeson and

Humphrey, 2006) to measure task and knowledge design characteristics using a seven-point Likert scale with anchors from 'strongly disagree' (1) to 'strongly agree' (7). Consistency coefficients were 0.95 (autonomy), 0.94 (task variety), 0.67 (complexity), 0.68 (problem solving) and 0.85 (specialisation).

*3.2.2. Intrinsic motivation*

Understanding the motivations that lead solvers to participate in crowdsourcing competitions is fundamental to the design of successful online contests (Ebner et al., 2009, Lampel et al., 2012). Motivations that influence solvers are based on cognitive benefits, social integrative benefits and personal integrative benefits, and hedonic or effective benefits (Katz et al., 1974). Intrinsic motivation is related to curiosity, eager to learn (Ryan and Deci, 2000a) and this is more towards natural tendency that comes from solvers' interest in crowdsourcing competitions. In this paper, we posit that a high level of intrinsic motivation would positively affect the participation intention for knowledge sharing. Consistent with the theory of work motivation (Amabile et al., 1994), intrinsic motivation was measured by using seven-scaled items describing perceived enjoyment and sense of achievement ($\alpha$= 0.77).

*3.2.3. Participation intention*

Participation intention refers to the solver's willingness to participate in prediction competitions. According to the Theory of Planned Behaviour (TPB) (Ajzen, 1991), the stronger the intention is the more likely it will be to participate. To measure solver's participation intention, respondents were asked three questions based on the participation intention scale used by Zeng et al., (2011) based on Alexandris et al., (2007) ($\alpha$= 0.80).

*3.2.4. Knowledge contributed effort*

Crowdsourcing studies show that contribution to online contests tend to follow a power law distribution in which only a small fraction of solvers participate a great deal whereas the vast majority of solvers 'lurk' in the background (Nielsen, 2013). Two measures of contributed effort were included in the study. First, we measured the total number of competitions entered by respondents. This data was provided by Kaggle for all respondents to the survey. Second, we considered the quality of submissions using Kaggle's user ranking based on users' performance in competitions. Kaggle's formula for competition points splits points equally among the team members, decays the points for lower ranked places, adjusts for the number of teams that entered the competition, and linearly decays the points to 0 over a two-year period (from the end of the competition).

*3.2.5. Mediator variable*

Trust in online communities is acknowledged to be important for creating a conducive environment in which solvers share their knowledge and expertise (Preece and Maloney-

Krichmar, 2003). We expect trust in the crowdsourcing platform to mediate the relationship between intrinsic motivation and participation intention. Trust in host is measured by using three-scaled items adapted from Kim et al. (2008) (α= 0.73).

## 4. Data Analysis and Results

We employed latent variable structural equation modelling (SEM) using the Maximum Likelihood algorithm in AMOS 21.0 to evaluate the model. In a prior phase, an exploratory factor analysis (EFA) was conducted in SPSS to uncover the most adequate measurement model in relation to our theoretical framework assumptions. The measurement model obtained was submitted to a confirmatory factor analysis (CFA) in order to assess its fit to the dataset used in SEM. Simultaneously, we estimated the structure within a series of dependence relationships between latent variables with multiple indicators while correlating for measurement errors (Hair et al., 2010). We calculated the following fit indices to determine how the model fitted our data: $X^2$ (chi-square), Goodness of Fit Index (GFI), Comparative Fit Index (CFI), Standardised Root Mean Square Residual (SRMR), Root Mean Square Error of Approximation (RMSEA). For GFI and CFI, values greater than 0.9 represent a good model fit, and for RMSEA values less than 0.07 indicate a good model fit, whereas values less than 0.1 are acceptable (Hu and Bentler, 1998, Kline, 2005).

### *4.1. Measure reliability and validity*

Drawing upon Hair et al. (2010), the psychographic properties of the measurement scales were assessed in terms of i) the individual items reliabilities, ii) convergent validity, and iii) discriminant validity. To achieve satisfactory scale assessment, several items were dropped from EFA (as shown in the Appendix). Reliability was established by means of Cronbach's (1951) alpha coefficient and composite reliability (CR). Convergent validity was measured by the average variance extracted (AVE). As shown in Table 1, all the scales showed a degree of reliability close to or above 0.7 (Nunnally, 1978). The adequacy of each multi-item scale for capturing its respective construct was subsequently examined. All the scales successfully passed the CR tests (close to or above 0.7) and the AVE for each construct was close to or above 0.5 (Fornell and Larcker, 1981). Therefore, these measures show moderate to high convergent validity (Kang et al., 2005).

To determine whether the constructs in our model were distinct from each other, we performed a test of the scales' discriminant validity following Fornell and Larcker (1981) recommended approach. The square root of the AVE of each scale variable in the model should be larger than the correlation coefficients with other measures. This condition was met in our study and we concluded that all scales were distinct from one another. The square root of AVE values are portrayed along the diagonal of Table 1.

**Table 1. Descriptive statistics and correlations for study variables[a]**

| Variable | Mean | S.D. | α | CR | AVE | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Autonomy | 6.330 | 0.750 | 0.950 | 0.954 | 0.805 | **0.897** | | | | | | | |
| 2. Task Variety | 5.670 | 1.040 | 0.940 | 0.942 | 0.805 | 0.499*** | **0.897** | | | | | | |
| 3. Complexity | 5.150 | 0.950 | 0.670 | 0.763 | 0.562 | 0.247** | 0.24** | **0.749** | | | | | |
| 4. Problem Solving | 5.860 | 0.820 | 0.680 | 0.692 | 0.432 | 0.426*** | 0.469*** | 0.55*** | **0.657** | | | | |
| 5. Specialisation | 5.360 | 1.040 | 0.850 | 0.835 | 0.561 | 0.042 | 0.055 | 0.193** | 0.099 | **0.749** | | | |
| 6. Intrinsic Motivation | 6.010 | 0.850 | 0.770 | 0.812 | 0.527 | 0.242*** | 0.229*** | 0.136 | 0.376*** | 0.044 | **0.726** | | |
| 7. Participation Intention | 6.110 | 0.860 | 0.800 | 0.828 | 0.712 | 0.196** | 0.236*** | 0.165 | 0.18** | 0.062 | 0.226** | **0.844** | |
| 8. Trust | 6.050 | 0.810 | 0.730 | 0.777 | 0.549 | 0.297*** | 0.296*** | 0.098 | 0.2** | 0.009 | 0.066 | 0.204** | **0.741** |

[a] n=222. Shown in bold on the main diagonal are the square root of AVE for each scale that should be higher than the correlation between that scale and the rest.
*** p<0.01; **p<0.05
AVE = average variance extracted; α = Cronbach' alpha; CR = composite reliability

*4.2. Common method bias*

Common method bias (CMB), also known as common method variance (Lindell and Whitney, 2001), is the 'variance that is attributable to the measurement method rather than to the constructs the measurement represent' (Podsakoff et al., 2003, p.879). Precautions were taken in the design of the study to avoid this bias. In addition to latent constructs, the study also makes use of available archival data to assess respondents' contributed efforts.

We conducted two *ex-post* tests to estimate this bias. First, CMB was assessed following the common latent factor (CLF) technique proposed by Podsakoff et al. (2003) which introduces a new latent variable in such a way that all observable variables in our eight factor model are related to it. A second test suggested by Lindell and Whitney (2001) was performed, the common marker variable (CMV) technique, which uses partial correlation and a marker (i.e., a presumed uncorrelated variable) to calculate CMB. We used *priori* identified variables with the lowest correlations to identify the marker variable. The uncorrelated variable enabled to evaluate the variance in factors, no obtaining unusual variances above the threshold of 50%. These results suggest that CMB is not a significant issue in this preliminary phase of the research.

*4.3. Structural model*

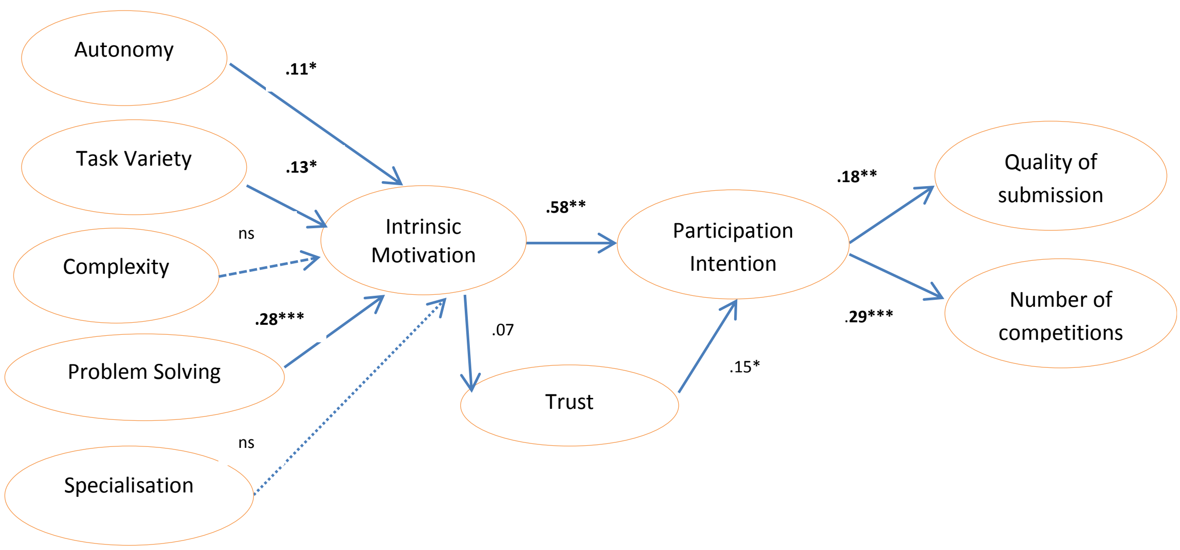
After having established the discriminant and convergent validity of the constructs, we tested the full structural model. Overall, our hypothesised model provided an acceptable fit for the data ($X^2$ [389] = 728.202; GFI = 0.823; SRMR = 0.143; RMSEA = 0.063; CFI= 0.914) and the majority of our hypotheses were supported by the data. Figure 2 shows the standardised path coefficients for the final model.

*4.4. Hypothesis testing*

Task and knowledge design characteristics explained 32% of the variance of intrinsic motivation. Task autonomy has a significant positive effect on intrinsic motivation ($\beta$ =0.11, p<0.10). Therefore, H1 is supported. Task variety also has a significant positive effect on intrinsic motivation ($\beta$ =0.13, p<0.10). Thus, H2 is supported. These results confirm that competition task characteristics are positively and significantly associated to intrinsic motivation. Task complexity is not significant, indicating that H3 is not supported. The effect of problem solving on intrinsic motivation is positive and significant ($\beta$ =0.28, p<0.01), supporting H4. Specialisation is not significant. Therefore, H5 is not supported. Overall, problem solving shows the strongest association with intrinsic motivation. This finding supports open source software research showing that intrinsically motivated developers derived satisfaction from the properties of the task (Calder and Staw, 1975, Deci, 1975). Data scientists are inherently curious and inspired by the creative process offered by prediction competitions as a means to gain a sense of competence and self-expression (Lakhani and Wolf, 2003).

H6 predicted a positive relationship between intrinsic motivation factors and participation intention. This hypothesis is supported (β = 0.58 p<0.05). Solvers participating in predictive modelling competitions are motivated by the enjoyment and sense of self-worth and achievement by sharing innovative knowledge more openly and effectively with peers, consistent with the notion of self-determination theory (Deci and Ryan, 1985). Finally, H7 and H8 relate solvers' participation intention to their contribution performance. Specifically, H7 predicts a positive relationship between solvers' participation intention and the quality/creativity of their submissions. This hypothesis is supported, as the path from participation to contribution quality is positive and significant (β =0.18, p<0.05). H8 posits a positive relationship between participation intention and the number of competitions entered. This hypothesis is supported (β =0.29, p=.000). Taken together, these findings indicate that seekers and crowdsourcing platforms need to understand what motivates or inhibit solvers for participating in crowdsourcing competitions. Solvers' performance in innovation contests determines the value that firms obtained from crowdsourcing.

**Figure 2. Structural Model**




*** p<0.01; **p<0.05; * p<0.10

*4.5. Mediating Role of Trust*

Our hypothesised model implies that trust in Kaggle, as a knowledge brokers between seeking companies and solvers, mediates the link between intrinsic motivation and participation intention. For the specification of the mediation link, we follow Baron and Kenny's (1986) procedure and find that all three steps are fulfilled. A mediation effect exists if the coefficient of the direct path between the independent variable (intrinsic motivation) and the dependent variable (participation intention) is reduced when the indirect path via the mediator (trust) is introduced in the model. As Table 2 shows, our mediation test showed a significant direct effect without and with mediator; the standardized beta of the direct effect was 0.698 ($p<0.05$), and 0.579 ($p<0.05$) after trust was introduced as a mediator. The amount of the relationship between intrinsic motivation and participation intention accounted by the mediator was 0.119 that represents 17% of the direct effect.

In order to confirm the mediating relationship and eventually determine the mediation type, we examined the significance of indirect effects using a bootstrapping method (with n= 2000 bootstrap resamples) recommended by Preacher and Hayes (2008). The advantage of bootstrapping is that it takes into account the skew of the distribution (Shrout and Bolger, 2002). Bias-corrected at 95% confidence intervals were calculated (Efron, 1987) and point estimates of indirect effects were considered significant if zero was not contained in the confidence interval. The bootstraping method reveals that the mediating effect is significantly different from zero at $p<0.5$, confirming a partial mediation effect of trust between intrinsic motivation and participation intention (Table 2).

**Table 2. Test of mediation**

| | Independent variable | Mediator | Dependent variable | Direct effects without mediator Standardized β | Direct effects with mediator Standardized β | Bootstrapping Indirect effect | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Value | S.E. | Lower | Upper |
| H9 | Intrinsic Motivation | Trust | Participation Intention | 0.698** | 0.579** | 0.023 | 0.016 | 0.001 | 0.027 |

**$p<0.05$

## 5. Discussion

Our results support the notion that the way virtual co-creation experiences are designed have the potential to ignite a sense of enthusiasm in participants and propel them to their peak levels of creativity (Füller et al., 2011). Drawing from the motivation through job design theory, we find that problem solving shows the strongest impact on intrinsic motivation (H4), underlying the particular traits of this crowdsourcing community in terms of the knowledge and ability demands required to participate in prediction competitions compared to ideas/concepts competitions. It is the knowledge dimension of the competition that particularly impacts on intrinsic motivation as solvers enjoy the challenge residing in the task participation process. The need to perform different tasks further challenge solvers to apply their abilities and skills (H2). Predictive modelling competitions also offer solvers a high level of autonomy to elaborate on their chosen methodologies leading in turn to greater intrinsic motivation as solvers enjoy a higher level of control over their actions during the competition (H1).

Intrinsic motivation was found to have a positive effect on participation intention (H6). Prediction competitions should be enjoyable and challenge solvers to excel while fostering a sense of community where participants can share ideas and build on each other's work. Otherwise, solvers could lose interest over time, even in activities they previously found motivating (Sansone and Smith, 2000).

Participation intention was found to have a strong significant impact on knowledge contribution (H7 & H8), consistent with the Theory of Planned Behaviour (Ajzen, 1991) and emerging crowdsourcing research (Zheng et al., 2011). Finally, the mediation test confirms a partial mediation effect of system trust between intrinsic motivation and participation intention (H9). These finding supports previous work concerning the importance of system trust in crowdsourcing communities (e.g., Leimeister et al., 2005). Crowdsourcing platforms need to develop trust-building strategies to positively influence knowledge contribution (Terwiesch and Ulrich, 2009, Quigley et al., 2007).

## 6. Conclusions

Open collaborative modes of innovation increasingly compete with and may displace producer innovation in many parts of the economy (Baldwin and von Hippel, 2011). These systems increasingly relate to socially significant domains, such as health support or eScience, offering individuals and organizations a fertile ground to engage in social value production enabled by new collaboration tools and digital technologies. However, it takes more than a technical infrastructure to make online communities a successful channel of innovation for companies (Wang et al., 2013). Crowdsourcing platforms need to understand how to encourage solvers' and seekers' participation to realise the benefits of crowdsourcing.

In this paper, we use Kaggle's data scientists community to identify the triggers of creative effort. Our findings support the premise that positive creative experiences lead to increased contributed effort (Füller et al., 2011, Garcia Martinez, 2015). We show the importance of competition design characteristics in stimulating solvers to submit novel and creative solutions. Kaggle's should attract intrinsically motivated solvers and try to raise intrinsic motivation and create an enjoyable environment by requiring solvers to perform a variety of complex tasks to further challenge solvers to apply their abilities and skills.

Studies reveal the importance of trust and social interaction to the exchange of knowledge in online communities (Hsu et al., 2007, Füller et al., 2011). Our study therefore extends knowledge by incorporating system trust as a positive influence in knowledge contribution.

*Limitations and Future Research*

We note several limitations in this study. First, our findings rest on data from a specialised knowledge community: Kaggle's data scientists community. Future research attempts should test the model with other online communities (i.e., brand communities, design communities) more focused on ideas/concepts generation. We believe that the strength of the knowledge dimensions of the competition could not be generalised to competitions where no specific technical knowledge is required. Second, the survey was sent to a selected group of solvers meeting pre-defined criteria and we only considered responses from respondents providing identifying membership details to allow us to model their answers alongside actual participation and performance data. These individuals may possess some characteristics that were not representative of the overall population. Third, we measured competition design parameters using self-reported data, instead of manipulating design features in an experiment. As well as using latent constructs, this study also made use of available archival data to assess respondents' participation to predictive modelling competitions and contribution performance.

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## Appendix A. Constructs, sources and item loadings

| | |
|---|---|
| **Autonomy** (Morgeson and Humphrey, 2006) | |
| **A1**. These competitions give me considerable opportunity for independence and freedom in how I develop my solutions | 0.88 |
| **A2**. These competitions allow me to decide on my own how to go about developing my solution | 0.87 |
| **A3.** These competitions gives me a chance to use my personal initiative or judgment in developing my solution | 0.91 |
| **A4.** These competitions allow me to make a lot of decisions on my own | 0.91 |
| **A5**. These competitions provide me with significant autonomy in making decisions | 0.92 |
| **Task Variety** (Morgeson and Humphrey, 2006) | |
| **TV1.** These competitions involve a great deal of task variety | 0.75 |
| **TV2.** These competitions involve doing a number of different things | 0.93 |
| **TV3**. These competitions require the performance of a wide range of tasks | 0.93 |
| **TV4.** These competitions involve performing a variety of tasks | 0.96 |
| **Competition Complexity** (Morgeson and Humphrey, 2006) | |
| **CC1.** These competitions require doing one task at a time (reverse scored). | 0.26 |
| **CC2.** These competitions comprise relatively uncomplicated tasks (reverse scored). | 0.85 |
| **CC3.** These competitions involve performing relatively simple tasks (reverse scored). | 0.95 |
| **Problem Solving** (Morgeson and Humphrey, 2006) | |
| **PS1**. These competitions require me to be creative. | 0.73 |
| **PS2.** These competitions often involve dealing with problems that I have not met before | 0.54 |
| **PS3.** These competitions require unique ideas or solutions to problems | 0.68 |
| **Specialisation** (Morgeson and Humphrey, 2006) | |
| **SP1**. These competitions are highly specialized in terms of purpose, tasks, or activities | 0.63 |
| **SP2**. The tools, procedures, materials, and so forth used on these competitions are highly specialized in terms of purpose. | 0.78 |
| **SP3**. These competitions require very specialized knowledge and skills. | 0.86 |
| **SP4**. These competitions require a depth of knowledge and expertise | 0.71 |
| **Intrinsic Motivation** (Amabile et al., 1994) | |
| **IM1.** I enjoy tackling problems that are completely new to me | 0.70 |
| **IM2.** I enjoy trying to solve complex problems | 0.92 |
| **IM3.** The more difficult the problem, the more I enjoy trying to solve it | 0.64 |
| **IM4.** I want to challenge myself to solve the problems in these competitions | 0.59 |
| **IM5.** Curiosity is the driving force behind much of what I do in these competitions* | |
| **IM6.** What matters most to me is enjoying what I do in these competitions* | |
| **IM7.** These competitions are fun and motivating* | |
| **Participation Intention** (Zeng et al., (2011) based on Alexandris et al., (2007) | |
| **PI1.** I will continue using Kaggle in the future | 0.97 |
| **PI2.** In general, I will continue to look for competitions to enter in order to satisfy my needs | 0.69 |
| **PI3.** In general, I will enter competitions hosted by any site (reverse scored)* | |
| **Trust in Host** (Kim et al., 2008) | |
| **T1.** Kaggle are trustworthy | 0.81 |
| **T2.** Kaggle keep their promises | 0.87 |
| **T3.** Kaggle keep solvers' best interests in mind | 0.50 |

* Items dropped in data analysis