MECHANISMS TO SELECT IDEAS IN CROWDSOURCED INNOVATION CONTESTS – A SYSTEMATIC LITERATURE REVIEW AND RESEARCH AGENDA

Research paper

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Abstract

Organizations use innovation contests to enable crowdsourcing for open innovation. While the crowd is able to generate large amounts of ideas in such contests, the challenge shifts to subsequent idea selection. This study systematically reviews the selection mechanisms that the literature has so far discussed for this purpose. Findings are structured using an analytical framework along selection process phases of preprocessing, shortlisting, selecting finalists as well as according to whether the crowd, small teams, automated or hybrid combinations of agents perform the selection. An agenda for further research is proposed based on these findings, emphasizing the need for research on selection mechanisms to process crowdsourced ideas.

Keywords: crowdsourcing, open innovation, selection mechanisms, innovation contest, literature reveiw, research agenda.

1 Introduction

Selecting a few out of large amounts of ideas is a paramount challenge in crowdsourced innovation contests (Blohm et al. 2013; Piezunka & Dahlander 2015). In such initiatives for open innovation, a divergent stage of crowdsourced idea generation (Poetz & Schreier 2012) is followed by a convergent stage to identify and select a small number of quality ideas (King & Lakhani 2013; Velamuri et al. 2017). Performing this idea selection typically requires the use of substantial amounts of resources. For example, an innovation contest at IBM required fifty senior executives and professionals to review, cluster, and identify valuable ideas from a pool of over 46,000 ideas down to a converged set of 31 'big ideas' in a week-long process (Bjelland & Wood 2008). At Cisco, a team of six full-time employees spent three months on the search for 40 semi-finalist ideas out of 1,200 ideas that entered the innovation contest (Jouret 2009). At Google, more than 3,000 employees were involved in reviewing over 150,000 ideas submitted to its tenth anniversary 'Project 10^100' and in a yearlong effort, they reduced them to 16 idea themes that the public could vote on (Google LLC 2009).

While it is characteristic for crowdsourced innovation contests that the crowd engages in idea generation through online platforms (Boudreau & Lakhani 2013), it is less obvious by whom and in what ways ideas are supposed to be selected when the traditionally closed approach to innovation is opened (Grönlund et al. 2010; Cooper 2008; Haller et al. 2017). One possibility is opening also the process of idea selection through crowdsourcing. However, companies might deliberately decide against further opening their innovation processes, including idea selection, and instead appoint internal teams to perform this task as they wish to remain in control on what ideas to pursue further (King & Lakhani 2013). Another option is automating (parts of) the idea selection process with the help of computational methods (e.g. Nagar et al. 2016). Yet another approach is combining different ways to select ideas for different purposes in a 'hybrid' fashion (e.g. Merz et al. 2016).

Prior literature reviews have either categorized different designs of innovation contests (e.g. Adamczyk et al. 2012), and general research perspectives and objects in the domain of open innovation (e.g. Bogers et al. 2017), or they have illustrated research on crowdsourcing without focusing on the specific context of innovation (e.g. Saxton et al. 2013; Zhao & Zhu 2014). There is, however, a growing stream of research that considers crowdsourcing applied for open innovation (Chiu et al. 2014). Within this stream, research has only recently begun to explore the convergent practices that exist in response to the selection of high numbers of ideas generated by the crowd during innovation contests (Velamuri et al. 2017; Haller et al. 2017). It is therefore the goal of this paper to review and synthesize existing literature on crowdsourcing for open innovation systematically. Doing so, this review focusses on the investigated selection mechanisms at play, defined in this work as approaches how to identify quality ideas in innovation contests. To analyze these mechanisms, a framework is proposed that structures the entire idea selection process in more detailed phases of preprocessing, shortlisting and selecting finalists as well as according to the agents performing the selection, which can be crowd, small teams, automated or hybrid combinations. By utilizing this analytical framework, the literature review synthesizes prior literature on *how* to select ideas (i.e. on the variety of selection mechanisms discussed in the literature thus far), as well as *when* (i.e. which selection process phase) and *by whom* (i.e. which selection agent) a certain selection mechanism (such as voting, single or multi-criteria rating scales, preference markets or natural language processing) can be employed. Based on these findings, a research agenda is proposed to lead the way for further research on idea selection in crowdsourced innovation contests by identifying issues that are currently under-researched or not yet addressed.

The remainder of this paper is structured as follows: The next section provides theoretical background on the concepts of crowdsourcing and open innovation. Then, the procedure for literature search and analysis is detailed, before the findings of this literature review are discussed and a research agenda is derived based on the review's findings. This paper concludes by emphasizing contributions and limitations of this systematic literature review.

2 Background

For incorporating innovation from outside their own boundaries, firms are relying on Information Systems (IS) to tap into the innovative capacity of an indefinite crowd of individuals (Boudreau & Lakhani 2013). As opposed to traditional modes of corporate innovation, where research and development activities are performed strictly inside corporate borders, the principle of 'open innovation' describes releasing these borders (Chesbrough 2003). Bringing innovations to market in this way, firms incorporate the input of outsiders for generating, developing and capitalizing on innovations. Contemporary open innovation models are frequently enabled by IS through a certain forming of crowdsourcing (Whelan et al. 2014), i.e. participative online activities that openly call upon a heterogeneous crowd of individuals to voluntarily undertake a given task (Estellés-Arolas & González-Ladrón-de-Guevara 2012). Examples for typical tasks are: to generate ideas for new products, to develop solutions to specific challenges or to evaluate existing suggestions. With such initiatives, firms apply crowdsourcing for open innovation in order to realize a competitive advantage, which thus constitutes the strategic use of IS (Majchrzak & Malhotra 2013).

The term 'crowdsourcing' was popularized in 2006 in an article by Howe (2006) to denominate an organization's practice of outsourcing tasks to the 'crowd' of individuals online – instead of executing those tasks internally. In the context of problem solving, this principle has been described as a 'broadcast search' process (Jeppesen & Lakhani 2010), transforming an agent's distant search (outside the scope of proximately available knowledge) into local search for members of the crowd who possess the necessary knowledge required to solve the problem (Afuah & Tucci 2012). This transformation requires to formulate the problem in an understandable way and to broadcast it publicly so that those members of the crowd capable of solving it can select themselves to participate (Afuah & Tucci 2012).

Crowdsourcing is an emerging, multifaceted and evolving concept accompanied by a plethora of practices, versatile areas of application and having various definitions (Estellés-Arolas & González-Ladrón-de-Guevara 2012). This paper follows Saxton et al.'s (2013) definition of crowdsourcing as "a sourcing model in which organizations use predominantly advanced internet technologies to harness the efforts of a virtual crowd to perform specific organizational tasks" (p. 3). While this definition emphasizes the involved crowds and online environments, it is indifferent to the context to which crowdsourcing is applied which makes it therefore compatible with other existing crowdsourcing definitions (Estellés-Arolas & González-Ladrón-de-Guevara 2012). This paper further concentrates on one specific application of crowdsourcing: open innovation (Majchrzak & Malhotra 2013).

Companies, which strive to bring innovations to market, have been observed to reshape the processes of generating, developing and capitalizing on innovations. These innovation processes, traditionally performed in internal research and development departments, are shifted into more 'open' innovation models that incorporate the input of outsiders (Chesbrough 2003). This concept of 'open innovation' has been subdivided in 'outside-in', 'inside-out' and 'coupled' processes (Chesbrough 2003; Gassmann & Enkel 2004). For this study, the outside-in process "enriching a company's own knowledge base through the integration of suppliers, customers, and external knowledge sourcing [to] increase a company's innovativeness" (Gassmann & Enkel 2004, p.1) is of particular importance as it explains the engagement of crowds in formerly closed innovation activities of organizations.

Next to Chesbrough (2003) who coined the term, open innovation research was pioneered by von Hippel (1986), who conceptualized lead users in product innovation and researched the innovation model of open source software development (von Hippel & von Krogh 2003). The underlying idea from these seminal works, proposing that openness in the innovation process may be advantageous compared to secretive and closed innovation due to an increased availability of creativity and knowledge, has then been transferred to all sorts of innovation processes (Rouse 2010). Likewise, the emerging research on open innovation has covered (intra-, inter- and extra-) organizational, industrial, regional and societal levels of analysis (Bogers et al. 2017). Researchers acknowledge, however, that the phenomenon of open innovation is not a theory per se and that extant research has not yet theorized the concept sufficiently (Bogers et al. 2017; Whelan et al. 2014).

Both concepts, crowdsourcing and open innovation, are overlapping when they serve the purpose of corporate innovation (Boudreau & Lakhani 2013). Due to this overlapping, "many have concentrated on the innovation facet and come to equate crowdsourcing with decentralized innovation" (Saxton et al. 2013, p.3). Yet, from a 'crowdsourcing' researcher's point of view, open innovation is one specific application of sourcing a task to the crowd (Chiu et al. 2014; Schlagwein & Bjørn-Andersen 2014). From an 'open innovation' researcher's point of view, crowdsourcing is one specific practice to implement outside-in open innovation (Bogers et al. 2017; Schlagwein & Bjørn-Andersen 2014). This led to blurred conceptual limits for either term (Estellés-Arolas & González-Ladrón-de-Guevara 2012; Whelan et al. 2014). This study reviews literature from both points of view that are relevant to idea selection at crowdsourced innovation contests (Adamczyk et al. 2012).

The overlapping of concepts manifests in crowdsourced innovation contests, which harness the willingness of individuals to share their ideas on innovations typically on an online contest platform. In these contests, the crowd generates ideas to enter the competition, ideas get selected and winners receive prizes (Adamczyk et al. 2012). Innovation contests have thus far been discussed regarding several aspects including participants' behavior (Bayus 2013), sources of motivation (Leimeister et al. 2009), roles (Füller et al. 2014), reward systems (Terwiesch & Xu 2008) and corporate strategy (Di Gangi & Wasko 2009). Online contest platforms may enable interaction among users and on ideas, so that the platform does not only allow for competition, but also for collaboration among participants (Hutter et al. 2011). The challenges that occur after the idea generation, i.e. when a contest is over, including the assessment and selection of ideas, have been subject to a small but growing body of literature, which this paper strives to shed light on.

3 Method

A systematic literature review was performed following a structured, sequential process to synthesize the existing evidence on idea selection and to identify gaps in current research, based on which a research agenda is developed (Okoli 2015; Webster & Watson 2002). The chosen approach is comprehensive, in that it collects as many relevant publications as possible in a rigorous and traceable way (vom Brocke et al. 2015; Okoli 2015). In accordance with the aim of this literature review, to examine how the extant literature has researched mechanisms to select crowd-generated ideas in innovation contests, an interdisciplinary review scope is taken which allows to identify relevant literature in a variety of research fields, such as innovation management or information systems. Therefore, literature was searched between October and November of 2017 in four interdisciplinary databases: Thomson Reuters' citation indexing service Web of Science (WoS, www.webofknowledge.com), EBSCOhost Business Source Premier (search.ebscohost.com), ScienceDirect (www.sciencedirect.com) and ProQuest (www.proquest.com). Additionally, literature search was extended to the Association for Information Systems Electronic Library (AISeL, aisel.aisnet.org) to cover leading publication outlets of the IS discipline (especially conference proceedings) which are not necessarily indexed in the databases from above.

The author explored several initial keywords and tested alternatives for their combinations and search operators, orienting on previous literature reviews on open innovation-related literature (e.g. Bogers et al. 2017) as well as crowdsourcing-related literature (e.g. Estellés-Arolas & González-Ladrón-de-Guevara 2012), in two iterations. In the first iteration, articles were searched that 1) incorporate crowds in any form and are in a crowdsourcing context (the used wildcard character (*) further allows for varying notations of crowdsourcing and closely related or synonymously used terms such as crowd creation, crowd processing, crowd voting, crowd solving, crowd wisdom, etc.), 2) are concerned with idea selection or synonymous activities, and 3) are related to innovation contests, including synonymous denominations such as competition, jam, tournament or prize as identified by Adamczyk et al. (2012). These groups of keywords were combined using AND operators, which yielded the search phrase (see Table 1) used to search within title, abstract and (where supported) keywords in the databases.

1st Iteration Search Phrase	*idea AND crowd* AND (select* OR screen* OR shortlist* OR filter* OR review* OR evaluat* OR converg* OR eliminat* OR reduc* OR vot* OR jud* OR assess*) AND (open OR contest OR competition OR challenge OR platform OR initiative OR tournament OR jam OR prize)*						
Database	Web of Science (WoS)	WoS Top IS Jour.[1]	WoS Basket of Eight[2]	EBSCO-host	Science Direct	ProQuest	AISeL
Search Hits	174	7	3	64	30	190	13
2nd Iteration Search Phrase	*idea AND (crowd* OR open) AND (select* OR screen* OR shortlist* OR filter* OR review* OR evaluat* OR converg* OR eliminat* OR reduc*)*						
Search Hits	-	18	8	-	-	-	30
Unique Total	**387**						

Table 1. Search Iterations, Phrases, Databases and Hits leading to a total of 387 papers.

In the second iteration, the search within IS publications indexed in WoS and AISeL was slightly widened to increase the number of search hits from this discipline. Table 1 details the search phrases used for both iterations and details the search hits per database yielding to a total of 387 unique publications in the set of papers to be reviewed. In order to filter for relevance and to exclude false positives from the search results, the titles and abstracts of all hits were screened next. Papers that did not manifest a context related to selecting crowdsourced ideas in innovation contests were excluded from further analysis. This screening resulted in a remainder of 49 papers selected as initially relevant. In the next step, these papers were examined in their full text. Authoritative sources as candidates for a subsequent backward and forward search (vom Brocke et al. 2015; Webster & Watson 2002) were deter-

[1] The leading 21 information systems journals according to the considerations of Lowry et al. (2013).

[2] The AIS Senior Scholars' selection of highly reputable publications in the IS discipline, the so-called 'Senior Scholars' Basket of Journals': www.aisnet.org/general/custom.asp?page=SeniorScholarBasket

mined. Papers in the result set not being research papers (e.g. editorials, literature reviews, work in progress) were excluded from further full text-based analysis.

Backward and forward search were performed using Google Scholar and 14 relevant papers were added to the full text-based analysis. Papers that seemed to be relevant from initial abstract-based reading but turned out not to be in this review's scope were eliminated, which led to a final set of 43 papers in this review. To analyze selection mechanisms in the final set of papers, this study applied an analytical framework that emerged during literature analysis, which consists of two context dimensions: a) selection process phases and b) selection agents. The proposed selection process phases resemble stages in a stage-gate process (Cooper 1990). While this concept originates from the traditional and 'closed' form of new product development, it can be applied to open innovation models (Grönlund et al. 2010). However, it considers the entire process from discovery to product launch, whereas the detailed selection process phases in this literature review have a more narrow scope and relate directly to the context of crowdsourced innovation contests with potentially very large amounts of crowd-generated ideas. By zooming in on idea selection, i.e. zooming in on the very beginning of the greater product development process, this first stage can be subdivided in:

- *Preprocessing*: preparatory measures (e.g. categorization, combination, etc.) prior to the actual evaluation of ideas, which do not necessarily reduce the amount of submitted ideas (e.g. Westerski et al. 2012; Westerski et al. 2013; Schaffhausen & Kowalewski 2015).
- *Shortlisting*: initial evaluation of ideas having a drastically reduced set of ideas (the shortlist) as outcome (e.g. Klein & Garcia 2015; Seeber et al. 2017).
- *Selecting finalists*: subsequent evaluation that begins with a limited amount of ideas in order to determine winners or candidates for implementation (Girotra et al. 2010; Chiu et al. 2014).
- *Entire selection process*: when a fine-grained distinction in the phases from above is not possible, e.g. because the selection process is seen as uniform.

To drive each of the selection process phases, the following selection agents can possibly be employed, which are defined in this review as:

- *Crowd*: an undefined, heterogeneous collection of individuals which may differ in its size, composition or levels of expertise (Saxton et al. 2013; Chiu et al. 2014) who self-select to participate (Afuah & Tucci 2012).
- *Small team*: a group of few appointed individuals who are associated with the innovation contest, such as platform moderators, experts or a jury board (Blohm et al. 2013; Ebner et al. 2009; Piller & Walcher 2006).
- *Automated*: algorithmic sets of computational instructions, which yield desired results in a finite number of moves to derive intelligence (Orlikowski & Scott 2015; Lopez Flores et al. 2015).
- *Hybrid*: pairwise combinations of the above agents that are intertwined during the selection process phase, i.e. automated and crowd, automated and small team or crowd and small team.

A paper was assigned to one of the four selection process phases according to the stated subject matter, research problem and a paper's purpose statements. In the exceptional case a paper contributed findings in more than a single phase, it was assigned to multiple applicable phases accordingly. Likewise, in cases where a paper exhibited several selection agents, it was attributed with all applicable agents. Both contextual dimensions of selection process phases and selection agents allow classifying the result set of research papers in this review and serve as a device for detailing the respective selection mechanisms under investigation in each paper. The findings of this literature analysis are presented and discussed in the next section.

In addition to the dimensions from above that are concerned with the subject matter of the research, the research design and employed methods were also analyzed in this literature review. Research methods found in the literature can be broadly distinguished in qualitative, quantitative and mixed method designs (Creswell 2009). Typical examples for methods in qualitative research designs are interpretative content analysis, case studies or ethnographies, whereas surveys and laboratory experiments represent typical forms of quantitative inquiry (Neuman 2014). Table 2 summarizes the research designs and methods found in the reviewed papers.

Research Design/Method and Paper Sources	Qty.
Qualitative	*3*
ethnographic study (Jarke 2017)	1
single case study (Lauto et al. 2013; Di Gangi et al. 2010)	2
Quantitative	*34*
experiment(s) (Blohm et al. 2016; Klein & Garcia 2015; Siangliulue et al. 2015; Duverger 2015; Westerski et al. 2012; Seeber et al. 2016; Seeber et al. 2017; Riedl et al. 2010; Sakamoto & Bao 2011; Bao et al. 2011; Seeber 2017; Görzen & Kundisch 2017; Kornish & Ulrich 2014; Magnusson et al. 2016; Riedl et al. 2013; Westerski et al. 2013; Blohm et al. 2011; Wagenknecht et al. 2017)	18
mathematical/structural modeling (Huang et al. 2014; Csaszar 2015; Hardas & Purvis 2012)	3
Natural Language Processing (Hoornaert et al. 2017; Schaffhausen & Kowalewski 2015; Rhyn & Blohm 2017; Walter & Back 2013; Nagar et al. 2016)	5
Natural Language Processing and network analysis (Rhyn et al. 2017)	1
network analysis (Stephens et al. 2016)	1
single case study (Mollick & Nanda 2016; Lauto & Valentin 2016; Schweisfurth et al. 2017; Merz et al. 2016; Di Gangi & Wasko 2009)	5
simulations and field experiment (Toubia & Florès 2007)	1
Mixed Methods	*6*
exploratory survey and interviews (Peisl et al. 2016)	1
field study/field experiment (Onarheim & Christensen 2012; Soukhoroukova et al. 2012; Magnusson et al. 2014)	3
simulation model and anecdotal case studies (Vuculescu & Bergenholtz 2014)	1
single case study (Schuurman et al. 2012)	1
Total	*43*

Table 2. Reviewed Literature by Research Designs and Methods.

4 Findings

Focussing on the selection mechanisms studied in the reviewed literature, this section presents and discusses the respective study results. Tables 3 to 6 detail the results of this literature analysis and are structured along the selection process phases of preprocessing (Table 3), shortlisting (Table 4), selecting finalists (Table 5) and the entire selection process (Table 6). Reviewed literature is grouped by the four different selection agents crowd, small team, automated or hybrid within each table. Among the 43 papers in the result set, more than half are concerned with shortlisting, whereas papers focusing on either preprocessing, selecting finalists or the entire selection process amount to roughly one-fifth each. In what follows, findings in each selection process phase are discussed.

4.1 Mechanisms for Preprocessing

Studies contributing selection mechanisms in the preprocessing phase, which comprise preparatory measures prior to the actual evaluation of ideas and do not necessarily reduce the amount of submitted ideas, are concerned with either small team, automated or hybrid selection agents. The contest-organizing firm, represented by a team of moderators on the contest platform, should provide information on its cost structure for implementing ideas. Signaling this information to ideators while the contest is running could decrease the amount of irrelevant ideas being submitted to a contest and therefore improve contest efficiency (Huang et al. 2014). To reduce the amount of ideas that need to be processed at later stages, one could also utilize Natural Language Processing (NLP) algorithms to screen ideas completely automated, which has been found to be an accurate approach for reducing redundant ideas (Schaffhausen & Kowalewski 2015) and capable of highlighting unique ideas in a dataset (Walter & Back 2013). Text-mining and machine-learning algorithms have been found to filter low quality contributions well based on textual characteristics such as length, terms used, readability and spelling errors (Rhyn & Blohm 2017).

Hybrid approaches have surfaced in the literature through combinations of automated and crowd agents for preprocessing. The crowd's feedback on the idea can be combined with automated approaches such as NLP to analyze an idea's content together with its contributor's history of past ideas, comments and tenure (Hoornaert et al. 2017). While the proposed text-mining and machine-learning algorithms can process the idea content and contributor history on the contest platform automatically and in real time, the study finds that it is desirable to incorporate the crowd's reaction and feedback to the idea into these analyses as well (Hoornaert et al. 2017). Similarly, the crowd's assessment of idea similarity can serve as input for a mapping algorithm to automatically generate spatial maps of ideas reflecting their diversity (Siangliulue et al. 2015). In contrast, an analysis of similarity can also be initially performed algorithm-based and thereafter handed to the crowd, which subsequently annotates relationships among similar ideas to summarize and aggregate similar ideas (Westerski et al. 2012; Westerski et al. 2013).

Agent	Selection Mechanism and Study Source
crowd	-
small team	• increasing the relevancy of submissions by providing precise information on cost structure to ideators (Huang et al. 2014)
automated	• analysis of (purely) textual characteristics (Rhyn & Blohm 2017) • analysis of idea similarity/redundancy (Schaffhausen & Kowalewski 2015; Walter & Back 2013)
hybrid	• automated analysis of idea content (distinctiveness), contributor characteristics and crowd feedback (Hoornaert et al. 2017) • crowd-based triplet comparisons (which of idea B or C is more similar to A); automated mapping of ideas in a spatial map (based on the crowd-compared distances between ideas) (Siangliulue et al. 2015) • automated analysis of idea similarity, crowd annotation of idea relationships (Westerski et al. 2012; Westerski et al. 2013)

Table 3. Mechanisms for Preprocessing in the Reviewed Literature by Agent.

4.2 Mechanisms for Shortlisting

In the shortlisting phase, i.e. the initial evaluation of ideas having a drastically reduced set of ideas as outcome, research has so far embraced the crowd, small teams, automated or hybrid (either crowd- and small team-based or crowd-based and automated) selection agents. Studies on single criterion rating scales find that a crowd can be superior to expert ratings (Kornish & Ulrich 2014) and that these scales are particularly suitable for the shortlisting phase, as this allows the crowd to distinguish across all (good and bad) ideas of the contest (Bao et al. 2011). Likewise, the use of multi-criteria rating scales allows replacing experts with crowd raters for shortlisting ideas (Magnusson et al. 2016). An experiment compared three different crowd-based selection mechanisms to shortlist ideas: a single rating scale and two different voting approaches giving individuals a fixed budget to vote for either high potential 'star' ideas or low potential 'lemons' (Klein & Garcia 2015). Among these three mechanisms, crowds eliminating bad ideas ('lemons') have the highest accuracy for shortlisting ideas (Klein & Garcia 2015). However, when the 'bag of lemons' approach is compared to single rating scale and up-/down voting mechanisms, 'bag of lemons' yields a higher user activity but also higher perceived frustration due to information overload (Wagenknecht et al. 2017). Furthermore, high quality ideas have been found to be more complex to evaluate by the crowd compared to low quality ideas when using single rating scales as the crowd is prone to be influenced by anchoring effects (Görzen & Kundisch 2017). Therefore, instead of using the crowd's rating of ideas directly, the variance of ratings can be used as a more adequate proxy to infer idea quality (Görzen & Kundisch 2017).

Preference or idea markets allow the crowd to evaluate ideas by valuating their potential and trading them similar to stocks in a (fictitious) market (Soukhoroukova et al. 2012; Lauto et al. 2013). In this context, it has been observed that the crowd's ability to process information from the idea content is limited, as overly complex and lengthy proposals are penalized (Lauto & Valentin 2016). Yet another alternative for crowd-based shortlisting is letting the crowd spend a (imaginary) budget on ideas in a mechanism comparable to crowdfunding. Here, funding decisions of an employee crowd inside an organization were found to be biased by organizational hierarchy: Especially for highly novel ideas, evaluators were influenced by their hierarchical similarity to ideators and this similarity affected their funding decision positively (Schweisfurth et al. 2017).

When the crowd is supposed to evaluate idea submissions through voting, this involves the risk of 'vote spamming', i.e. the abusive use of the voting mechanism by individuals or groups within the crowd (Hardas & Purvis 2012; Schuurman et al. 2012). Weighting votes based on voter history and collective opinion can improve crowd voting as it controls for spamming (Hardas & Purvis 2012). Three studies comparing crowd voting with small team-based idea assessment yield mixed results: One finds significant correlations of binary voting results derived from of a crowd (consisting of experienced individuals) and a small team of experts (Onarheim & Christensen 2012). Another study using multi-criteria rating scales finds underwhelming agreement between expert team ratings and crowd voting (Schuurman et al. 2012). In yet another observed case, the crowd failed to shortlist ideas with a simple voting mechanism due to the fact that it did not contain specific evaluation criteria. In the same case, an expert team was successful in shortlisting ideas by utilizing multi-criteria rating scales (Jarke 2017).

For shortlisting in small teams of experts, the use of intuition, i.e. the absence of formally specified assessment criteria, can simplify and fasten the process, as long as domains of expertise and assessment instructions are validated (Magnusson et al. 2014). When small teams are asked to shortlist ideas, team members can engage in the convergence of ideas, that is, to reduce and clarify ideas within the team: Studies in this context have shown that teams being facilitated by a team leader who exerts formal control on the team perform superior to self-managed teams (Seeber et al. 2016), facilitated teams have a higher extent of information elaboration than non-facilitated teams (Seeber 2017), and that teams converging on crowd-generated ideas (as opposed to self-generated ideas) are subject to more challenging social exchange processes (Seeber et al. 2017).

Automated approaches to shortlisting involve the automated analysis of network structures and textual characteristics of contributions on a contest platform, where ideators with weak network ties are more likely to contribute useful ideas, which are then further enriched by other members of the crowd (Rhyn et al. 2017). Similarly, analyzing textual data of ideas as well as ideator and crowd interactions with the submitted idea has been found to reduce the load and effort required for subsequent selection of finalists (Nagar et al. 2016).

The literature discusses hybrid approaches to shortlisting as either crowd-based and automated (Toubia & Florès 2007; Sakamoto & Bao 2011) or crowd- and small team-based (Merz et al. 2016). For crowd-based and automated shortlisting, an algorithm could allocate small sets of ideas out of a large idea pool to individuals in a crowd based on previous evaluations (Toubia & Florès 2007). This algorithm should focus on ideas being most likely misclassified as 'top' or 'bottom' and could therefore prevent a premature exclusion of misclassified ideas (Toubia & Florès 2007). Within a different genetic algorithm system, a crowd-based single scale rating is followed by a pairwise combination of ideas within the shortlisting phase. In this system, idea pairs are selected automatically by a tournament selection algorithm, which receives the initial crowd rating as an input (Sakamoto & Bao 2011). In crowd- and small team-based shortlisting, ideas were found more likely to be shortlisted, when they were well-developed by the ideator and received appreciation by the crowd as well as the selection team while the contest was still running (Merz et al. 2016).

Agent	Selection Mechanism and Study Source
crowd	• voting (Jarke 2017; Schuurman et al. 2012), up- and down-votes (Hardas & Purvis 2012), binary voting (Onarheim & Christensen 2012) • preference/idea market (Lauto & Valentin 2016; Lauto et al. 2013; Soukhoroukova et al. 2012) • funding decision (Schweisfurth et al. 2017) • single criterion rating scale (Kornish & Ulrich 2014), single criterion rating scale, voting with fixed budget ('bag of stars', 'bag of lemons') of votes (Klein & Garcia 2015), up- and down-votes, single rating scale, voting with fixed budget ('bag of lemons') (Wagenknecht et al. 2017) • single criterion rating scale as part of a genetic algorithm system (Bao et al. 2011) • variance of ratings based on a single criterion rating scale (Görzen & Kundisch 2017) • multi-criteria rating scales (Magnusson et al. 2016)
small team	• multi-criteria rating scales (Jarke 2017; Schuurman et al. 2012) • intuition without specific criteria, multi-criteria rating scales (Magnusson et al. 2014) • convergence (reduction and clarification) of ideas: ○ facilitated by a team leader (Seeber et al. 2016) ○ on self-generated or crowdsourced ideas (Seeber et al. 2017) ○ crowdsourced ideas with or without facilitation (Seeber 2017)
automated	• analysis of network ties of ideator, text mining and topic modeling for contribution novelty, knowledge recombination (Rhyn et al. 2017) • analysis of text characteristics, crowd activity and contributor actions (Nagar et al. 2016)
hybrid	• crowd-based evaluation; automated allocation of ideas to evaluators adaptively based on previous evaluations (Toubia & Florès 2007) • crowd-based evaluation with single rating scale and pairwise combination of ideas; automated tournament selection of idea pairs as part of a genetic algorithm system (Sakamoto & Bao 2011) • crowd-based idea development and community appreciation; small team-based early host appreciation (Merz et al. 2016)

Table 4. Mechanisms for Shortlisting in the Reviewed Literature by Agent.

4.3 Mechanisms for Selecting Finalists

For selecting finalists, which comprises the evaluation of a limited amount of ideas in order to determine winners or candidates for implementation (Girotra et al. 2010; Chiu et al. 2014), extant literature has so far explored the crowd and small teams as selection agents. When comparing multi-criteria rating scales and preference markets for crowd-based selection of finalists, rating scales yield more accurate outcomes and a higher decision quality than preference markets due to the rating scales' higher perceived ease of use (Blohm et al. 2016; Blohm et al. 2011). Likewise, it is easier for the crowd to evaluate ideas with lesser potential and the crowd's task should be framed with a focus on eliminating low quality ideas accordingly (Blohm et al. 2016). For different granularities of crowd-based mechanisms to select finalists, the more granular multi-criteria rating scales outperform less granular, simpler mechanisms (Riedl et al. 2010; Riedl et al. 2013). Further, as little as 20 ratings per idea can be sufficient to create robust ranking aggregates (Riedl et al. 2013). Prediction voting is proposed as a mechanism for selecting finalists in a genetic algorithm system, where the crowd is supposed to predict which idea out of a pool of ideas is going to win the contest (Sakamoto & Bao 2011; Bao et al. 2011). Prediction voting has been found to be appropriate when there still exist many poor quality ideas in the idea pool and less adequate when only good submissions remain out of which the very best needs to be determined (Bao et al. 2011).

When crowd-based funding decisions on a crowdfunding platform are compared with the multi-criteria ratings performed by a small team of experts, generally agreeing selection decisions of crowd and experts have been found (Mollick & Nanda 2016). This suggests that a crowd-based selection mechanism comparable to crowdfunding, where submissions need to reach a certain threshold of funds by the crowd, can complement expert decisions especially when the crowd consists of (potential) end users (Mollick & Nanda 2016). Similarly, multi-criteria rating scales can be used by a small team for selecting finalists out of a shortlist that resulted from a preceding crowd-based preference market (Lauto et al. 2013).

Agent	Selection Mechanism and Study Source
crowd	• funding decision (Mollick & Nanda 2016) • multi-criteria rating scales, preference market (Blohm et al. 2016; Blohm et al. 2011) • single rating scales, multi-criteria rating scales (Riedl et al. 2010; Riedl et al. 2013) • prediction voting as part of a genetic algorithm system (Bao et al. 2011; Sakamoto & Bao 2011)
small team	• multi-criteria rating scales (Mollick & Nanda 2016; Lauto et al. 2013)
automated	-
hybrid	-

Table 5. Mechanisms for Selecting Finalists in the Reviewed Literature by Agent.

4.4 Mechanisms for the Entire Selection Process

Studies exist that do not allow for a fine-grained distinction in the selection process phases from above, e.g. because the process is seen as uniform. Studies that consider the selection process in its entirety are concerned with either crowd or hybrid selection agents. A network analysis of the relationships between voters from an employee crowd and ideas revealed a concentration of votes to few highly popular ideas, while most ideas received only a little number of votes (Stephens et al. 2016). This can lead to self-reinforcement among the popular ideas becoming even more popular in return. In similar terms, the voting behavior differed with only a few employees voting for many different ideas and the majority of employees voting for just a small number of ideas (Stephens et al. 2016).An experiment on the relationship between an idea's positive or negative wording, customer satisfaction and crowd voting with a fixed budget of votes on pairs of ideas demonstrated that emotions may interfere with the voting on ideas, as satisfied voters tend to reject negatively worded ideas while dissatisfied voters opt in favor of these (Duverger 2015). With respect to finding the optimal crowd size for voting, research postulates that the largest possible crowd is rarely desirable. Instead, the accuracy of individuals of the crowd mattered more than a large crowd, which is only needed to compensate for low accuracy (Csaszar 2015). A rather small crowd size is preferable when a crowd is to be incorporated in the selection of disruptive ideas to effectively complement a firm's inside perspective (Peisl et al. 2016). One study analyzed four different strategies to the selection process, which can be selecting 'best' ideas, proportional, tournament or generalized rank selection, bearing the general tradeoff of either eliminating submissions with low potential early on or maintaining diversity to reach high quality solutions (Vuculescu & Bergenholtz 2014). It has been found that selecting best ideas was inferior to all other strategies because this discarding of non-performant submissions eliminated diversity too early and hindered the exploration of the entire solution space through refinements and combinations (Vuculescu & Bergenholtz 2014).

Agent	Selection Mechanism and Study Source

crowd	• voting (Stephens et al. 2016)
	  ○ voting with fixed budget of votes on pairs of ideas (Duverger 2015)
	  ○ determining optimial crowd size for voting (Csaszar 2015)
	• evaluation of disruptive ideas as opposed to incremental innovations (Peisl et al. 2016)
	• strategic alternatives: best ideas, proportional, tournament, generalized rank selection (Vuculescu & Bergenholtz 2014)

small team	-
automated	-
hybrid	• crowd-based voting; small team-based engaging of lead users, creating of user toolkits (Di Gangi et al. 2010; Di Gangi & Wasko 2009)

Table 6. Mechanisms for the Entire Selection Process in the Reviewed Literature by Agent.

Further current challenges in the selection process are identified as the volume of submissions, duplicate ideas, influence of minority opinions and an a firm's urgency to respond to the crowd (Di Gangi et al. 2010). In response to these challenges, the crowd should be given a say through voting, the team of moderators should be put in charge of engaging lead users and user toolkits should be created to allow self-governance in addition to mere voting for selecting ideas (Di Gangi et al. 2010).

5 Research Agenda

By providing a detailed overview on selection mechanisms, agents and phases, this literature review illustrates the extent to which research has to date investigated the challenge of selecting ideas out of large amounts of crowd-generated ideas. Introducing an analytical framework, this study elicits gaps where the current discourse on idea selection is either lacking the perspective of a selection agent in a certain phase of the selection process entirely (see gaps in Tables 3-6), or has not yet explored selection phase or agent-specific issues sufficiently. This is evident especially when findings from the existing literature are conflicting or inconclusive. Based on this study's analysis of prior literature along selection process phases and agents, a research agenda for scholars in the IS domain is proposed. By considering that either selection agent (crowd, small team, automated, or hybrid) is situated in a socio-technical system, the agenda adopts the perspective on IS as interactions between technology and social setting (Lee 1999). Table 7 gives an exemplary and non-exclusive overview on relevant questions for further research in this agenda.

Phase	Agent	Examples of Research Questions
pre-processing	crowd	How can the crowd be appointed to effectively preprocess ideas (e.g. to categorize or detect similarities) prior to the actual evaluation of ideas?
	small team	How can the subsequent phases of the selection process benefit from small teams that are engaged already in the preprocessing phase of idea selection?
	automated	Which kinds of preprocessing can reliably and accurately be performed by automated agents and how should such automated algorithms be designed?
	hybrid	How to orchestrate the collaboration among crowd, small team and automated agents in the preprocessing phase of idea selection?
shortlisting	crowd	Which mechanisms serve the crowd best to shortlist ideas? Should the same crowd that generated ideas be part of shortlisting? How to compensate flaws of existing mechanisms?
	small team	How can small teams be supported to render the shortlisting of ideas more efficiently and effectively?
	automated	What are promising strategies for automated shortlisting of ideas? How to set meaningful thresholds that determine the shortlist's size?
	hybrid	How can combinations of crowd, small team and automated agents work together in order to shortlist ideas?
selecting finalists	crowd	Which mechanisms allow a crowd to identify the best idea(s)? Should the same crowd that generated ideas be part of selecting finalists? How to compensate flaws of existing mechanisms?
	small team	Which mechanisms allow a small team to identify the best idea(s)?
	automated	How can automated agents identify an idea's quality characteristics, sense and intention in order to select finalists?
	hybrid	What approach is superior for selecting finalists - single agents (either crowd, small team or automated alone) or combinations of complementary agents?

Table 7. Research Agenda Question Examples by Selection Process Phase and Selection Agent.

Research on the crowd as selection agent has so far investigated how the crowd can be used for shortlisting and selecting finalists, but did not yet consider the preprocessing phase of idea selection. It is therefore important for future studies to find answers to how the crowd could be appointed for an effective preprocessing of ideas prior to their evaluation. Research suggesting to draw on the crowd for shortlisting ideas has discussed shortcomings with the use of single criteria rating scales (e.g. Görzen & Kundisch 2017) and crowd voting (e.g. Hardas & Purvis 2012; Schuurman et al. 2012). Further research could attempt to find possible solutions to remedy or mitigate present shortcomings. Additional experiment-based research is needed, which tests crowd-based approaches for idea selection across different crowdsourced settings and multiple datasets to determine whether proposed selection mechanisms are able to achieve the desired results across different contexts. Studies replicating current findings in different innovation contest settings could further enhance the current knowledge base.

Similarly, further research on small teams should attempt to cover a wider variety of cases of crowdsourced innovation contests, augmenting findings of the few single case studies that exist until now (cf. Table 2). Multiple-case study research designs could therefore draw on a set of qualitative methods such as observations, interviews and focus groups in order to understand the functioning of small teams better not only when it comes to selecting finalists, but also when shortlisting or preprocessing large amounts of ideas. This would not only contribute to an improved understanding of current challenges during idea selection, but could also be helpful for designing specific tools and facilitation techniques that support teams in their tasks. Studying how small teams currently perform tasks along the selection process phases, e.g. how selection criteria are interpreted and applied in a team, may further offer implications for transferring team practices to crowd-based or automated agents.

Prior research on automated selection agents has mostly been concerned with aspects for the preprocessing phase of idea selection. Future work on automated selection agents should further intensify researching this promising avenue on preprocessing, but also aim to contribute strategies for shortlisting and selecting finalists. In this vein, NLP algorithms need to be further developed and refined to optimize automated preprocessing. The processing of (meta-)data that is available on a contest platform and contains information on submitted ideas, ideators and the crowd's interactions could be enriched with information from sources outside of the contest platform, e.g. by performing automated web searches. This may be useful e.g. to assess an idea's uniqueness not only within the limited setting of a single contest, but within drastically broadened scopes.

In addition to researching the selection agents crowd, small team and automated in separation, further research is needed that is dedicated to the hybrid combinations of selection agents for preprocessing, shortlisting and, since there exists none to date, especially for selecting finalist ideas. Work in this realm needs to be concerned with the design, testing and evaluation of potentially highly complex selection mechanisms, therefore deriving crucial implications and recommendations on improved selection practices through proof of concept, proof of value and proof of use research contributions (Nunamaker et al. 2015).

Due to the socio-technical setting of crowdsourced innovation, scholars in the IS discipline are ideally suited to pursue this suggested agenda for selection mechanisms by concentrating on the interactions between technology and its embedded social setting (Lee 1999; Baskerville & Myers 2002). In this sense, it is necessary to establish an understanding on the interdependencies of technology, the crowd, involved organizations and outcomes when investigating crowdsourcing for open innovation, instead of examining them in isolation. Accordingly, Majchrzak and Malhotra (2013) argue that instead of taking IS for granted, their role as "not just an enabler but rather […] a shaper that optimizes open innovation in general and crowdsourcing in particular" (p. 257) requires further research. Understanding this role comprises not only how IS enables mechanisms for the automated selection of ideas, but also how small teams and the crowd can be supported by IS for preprocessing, shortlisting and selecting finalists in innovation contests.

6 Conclusion

This study has introduced an analytical framework in order to review extant literature on the selection mechanisms for crowdsourced innovation contests and derived a research agenda based on the findings. The contributions of this study are threefold: First, following a structured procedure, it provides an overview of literature on selection mechanisms in the context of crowdsourcing for innovation in a systematic way. Second, it introduces an analytical framework consisting of two dimensions, a) selection process phases and b) selection agents, which allow a structured analysis of the selection mechanisms. Third, a research agenda is proposed based on these findings, which serves as a guide for IS scholars, pointing towards under-researched and void areas that are worthwhile for further research.

Like any research, this literature review has its limitations. First, the scope of this study is limited to publications indexed in five leading databases (cf. Section 3). While this choice may exclude some potentially relevant papers from the result set, a forward and backward search was performed in order to comprehensively cover relevant publications in the result set, while maintaining the review's focus. Second, the choice of dimensions for analysis resulting in the applied analytical framework is not free from subjective assessment. While other researchers might emphasize different dimensions for conceptualizing this type of research, the proposed analytical framework has demonstrated to be robust for systematically categorizing the wide variety of selection mechanisms found in the literature. Furthermore, the findings of this review are presented in a traceable way, indicating the literature sources for each selection mechanism in the result set. Third, there exists a certain ambiguity in the definitions of crowdsourcing and open innovation, which affects the search results when using (parts of) these terms as keywords. While it can be argued that both concepts have overcome the 'buzzword' stage and are coherently used, there exist related terms such as 'co-creation' or 'user innovation' used interchangeably with crowdsourcing and open innovation in the literature. Aside from keyword search, backward and forward search were employed to mitigate this shortcoming.

To the extent of this author's knowledge, no other study has so far reviewed the emergent stream of literature on selection mechanisms in crowdsourced innovation contests. This work has therefore synthesized the findings of 43 relevant research papers to identify gaps and point out avenues for further research. The fact that a relatively little amount of studies has been published thus far and that none of the papers have been released earlier than 2007 indicates that research on this phenomenon is only beginning to unfold. At the time of this writing, the majority of existing studies have targeted the shortlisting of ideas in an innovation contest, while fewer studies exist on preprocessing and selecting finalists. Likewise, most have explored the role of the crowd for this selection task, whereas fewer studies have so far concentrated on small teams, automated or hybrid agents. Studies have begun to embrace different concepts of automation recently, but largely for the purpose of preprocessing ideas. Further insights on introducing automation to the selection process need to be developed in the context of shortlisting and selecting finalists. Eventually, future research needs to specify the conditions under which idea selection is successful in terms of what agent (or hybrid combinations of agents) should be employed for which selection process phase. This present work intends to serve as a starting point, inviting scholars to advance the knowledge base on selection mechanisms further.

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