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The state-of-the-art of crowdsourcing systems: A computational literature review and future research agenda using a text analytics approach

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ABSTRACT

Crowdsourcing effectively harnesses diverse skills and perspectives of crowds beyond organizational, geographical, and cultural boundaries. Organizations are gaining invaluable insights through crowdsourcing across diverse domains. This study reviews the growing academic literature on crowdsourcing using advanced topic modeling, an approach to unraveling key themes latent in the literature. Following a systems approach, we adopted inter- and intra-systems perspectives to identify distinct crowdsourcing models and their interrelated components based on a text analysis of the crowdsourcing literature. The paper elucidates the intellectual foundations of crowdsourcing as represented in the literature and offers suggestions for pursuing research that will extend its conceptual boundaries.

1. Introduction

The expanding accessibility and sophistication of information technology (IT) enables organizations and even individuals to leverage the creativity, sensemaking, knowledge, and skills of diverse and dispersed individuals known as *crowds*. Crowds are people who are typically found outside organizational boundaries,[1] in that they do not have formal or strong ties to the organization or individuals seeking their involvement. They can generate value by providing data, solving challenging problems, or donating other resources (such as money, as in *crowdfunding*). The practice of involving crowds in the provision of goods or services is known as *crowdsourcing* [1].

Crowdsourcing has been successfully used in a variety of domains, including science, IT development, marketing, education, healthcare, and manufacturing. It offers several benefits to clients, including faster design and/or prototyping, higher quality of products/services, faster response to market conditions, better handling of tedious tasks, access to a large and diverse pool of external talent, and lower costs.[2] At the same time, there are notable challenges in leveraging crowds, including the need for evolving effective incentive mechanisms and a more efficient submission management process, avoiding the potential loss of control, and ensuring data and solution quality (e.g., prediction accuracy, design quality, labeling accuracy) [2–5].

To understand and guide the practice of crowdsourcing, researchers from different disciplines, including information systems (IS), have begun to develop frameworks and taxonomies. While these studies have made significant contributions to the crowdsourcing literature, the lack of consistency among the taxonomies as well as the absence of a holistic perspective to investigate various crowdsourcing phenomena present opportunities for broader and deeper analysis and insight. For example, previous reviews of the literature in the domain have mainly focused on individual aspects of crowdsourcing systems, such as crowd platform governance [6], crowdsourcing definitions [7], factors influencing the decision to crowdsource [8], or a specific type of crowdsourcing model. Such a narrow focus precludes us from seeing the vast potential of crowdsourcing. There are, however, a few notable exceptions (e.g., [9, 10]). Zhao & Zhu [10] conducted a review of early crowdsourcing literature and suggested future research directions that reflected three perspectives, namely, a participant's perspective (e.g., motivations and behaviors of individuals), an organization's perspective (e.g.,

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[1] Some consider informal organizational groups to be "internal crowds" [130]

[2] https://www2.deloitte.com/content/dam/Deloitte/uk/Documents/Innovation/deloitte-uk-crowsourcing-using-the-crowd.pdf

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crowdsourcing adoption, implementation and governance, quality and evaluations), and a system's perspective (e.g., incentive mechanisms, technology issues). In their recent review of the crowdsourcing literature, Nevo & Kotlarsky [9] identified three main streams of crowdsourcing literature: a) the crowdsourcing component (e.g., motivation, performance); b) the stakeholder perspective (seeker, solver, or platform); and c) the project lifecycle view (e.g., initiation, execution, closure). Ghezzi et al. [11] articulated an input-process-output framework based on their literature review, while Assis Neto & Santos [12] discussed three dimensions of crowdsourcing projects: task execution, quality management, and platform usage. Modaresnezhad et al. [13] proposed a framework to distinguish applications based on the answers to four key questions: Who? Why? What? How? Despite these efforts, a European Union report on crowdsourcing laments the disagreements in approaches to crowdsourcing and concludes that the concepts remain "rather elusive."[3]

Although the studies have begun to explore the boundaries of crowdsourcing, a more holistic approach to recognizing the different types of crowdsourcing models and what has been studied within each model would deepen our understanding of the extant literature and provide a roadmap for future research. We followed the principles of problematization by Alvesson and Sandberg [14] to provide a critical analysis of the current crowdsourcing literature and generate new avenues for future studies. Specifically, our research endeavors to address the following questions: a) What are the primary types of crowdsourcing models represented in the current information systems literature? b) What are the similarities and differences among these distinct models in terms of the nature of the task and the role of stakeholders? c) What has been studied about these distinct models and what are the potential future research problems related to each model considering its components?

Although crowdsourcing is a multi-disciplinary domain, our study focuses primarily on articles published in key IS and business journals to elucidate the state of crowdsourcing research. Specifically, the current study uses a combination of text analytics and subject matter experts' opinions to understand the scholarly landscape of crowdsourcing. In recent times, researchers have employed advanced text analysis and unsupervised learning techniques such as topic modeling to uncover topics latent in the conceptual structure of a discipline [15]. Unlike a manual review process, which can be time-consuming (and thus tends to be limited in scope), text analysis techniques facilitate a holistic analysis of a larger sample of articles [16]. Furthermore, these techniques are unobtrusive, more inclusive, and avoid some sources of subjectivity and biases that humans tend to exhibit. Given these advantages of text analysis for the purposes of conducting a review, our study uses Latent Dirichlet Allocation (LDA), Non-Negative Matrix Factorization (NMF), and BERTopic, which is based on Bidirectional Encoder Representations from Transformers (BERT), to conduct a comprehensive review of the crowdsourcing literature in organizational literature. LDA is a popular probabilistic topic modeling approach [17] widely used in academic research (e.g., [15]). BERTopic takes advantage of recent developments in Natural Language Processing (NLP) by clustering semantically rich embeddings of text to obtain topics [18]. We validate the results using a semi-supervised topic modeling approach called Anchored Correlation Explanation (Cor-Ex) [19].

In contrast to many of the previous studies that reviewed crowdsourcing, we adopted a theoretical perspective to guide our analysis and interpretation. We used a combination of inter-system and intra-system perspectives to categorize the crowdsourcing literature and identify research gaps. Specifically, the inter-system perspective helps to compare and contrast different types of crowdsourcing models. Our topic-based literature review revealed four main types of crowdsourcing models: contest model, micro-tasking model, idea generation model, and observational model. Distinguishing among the different types of crowdsourcing models using such a holistic approach has several theoretical and practical benefits. For example, our framework helps researchers identify the boundary conditions for each type of system model and its associated research gaps. In addition, our framework enriches the evolving academic discourse on the theory of crowdsourcing and helps organizations select the most effective crowdsourcing model contingent on the task. For example, the quality of the solution may be the primary requirement for a particular task, while another task may require crowd participants to generate as many solutions as possible; the first case suggests a contest model, whereas the second would benefit more from observational crowdsourcing. From the perspective of clients, these are essential considerations for identifying the most likely solvers for a given task. Furthermore, crowd participants' motivations in different crowdsourcing models naturally vary, and our framework suggests important new ways to understand the motivational dynamics of projects so that organizations can better attract and retain crowds. For example, in a typical crowdsourcing contest model, winning the reward is the key motivation behind a solver's effort. On the other hand, prosocial motives are likely to contribute to observational models that address community issues such as disaster management efforts.

From the intra-system perspective, a more expanded approach is required when studying a particular crowdsourcing system. Drawing on Ackoff's systems thinking approach, we argue that individual components of the crowdsourcing system should not be examined in isolation but should be viewed holistically when evaluating total system performance [20]. For example, several studies in crowdsourcing contests have investigated the effect of individual components such as reward structure, feedback, and gaming elements on the outcome of a crowdsourcing system. However, these interrelated components comprise a system, and it may be more insightful to investigate the whole rather than the individual parts. From a systems perspective, a siloed approach that privileges the parts of a system rather than the relationships among the parts can lead to sub-optimal performance [21]. The systems approach advocated by Ackoff [20], Churchman [22], and Van Gigch [21], among others, suggests that an understanding of the various components of crowdsourcing and their interactions is critical to our ability to harness the enormous potential of the crowdsourcing phenomenon.

The remainder of this paper is organized as follows. The following sections provide an overview of crowdsourcing systems and the relevant literature. Subsequently, we describe the publication selection process and research methodology. Next, we discuss the findings of content analysis from inter- vs. intra- system perspectives, identify gaps in the literature, and propose future research directions, including more specific research themes and questions.

2. Background: crowdsourcing definitions, reviews and taxonomies

2.1. Understanding crowdsourcing

Before conducting our analysis, we first identify the nature and scope of crowdsourcing.

Early definitions view crowdsourcing as the means through which organizations outsource their tasks to a broader community of otherwise unaffiliated participants. Drawing from Howe [23], García et al. [24] refer to crowdsourcing as a "process of taking tasks that have traditionally been performed by employees or contractors and outsourcing them through an open call to an undefined group" (p. 373). With the emergence of a wider range of crowdsourcing models and applications, scholars proposed several definitions that apply to specific contexts. Recognizing the need for a broader definition of crowdsourcing, Estellés-Arolas & González-Ladrón-De-Guevara [7] suggested the following integrated characterization of crowdsourcing that is informed

[3] https://op.europa.eu/en/publication-detail/-/publication/85558431-cfb4-4ff7-817d-5ad1338dc4b1

by previous definitions:

> *Crowdsourcing is a type of participative online activity in which an individual, an institution, a non-profit organization, or a company proposes to a group of individuals of varying knowledge, heterogeneity, and number, via a flexible open call, the voluntary undertaking of a task. The undertaking of the task, of variable complexity and modularity, and in which the crowd should participate bringing their work, money, knowledge and/or experience, always entails mutual benefit. The user will receive the satisfaction of a given type of need, be it economic, social recognition, self-esteem, or the development of individual skills, while the crowdsourcer will obtain and utilize to their advantage what the user has brought to the venture, whose form will depend on the type of activity undertaken.* (p. 197)

Definitions of crowdsourcing are not limited to the practitioner and academic literatures. It is notable that public agencies and governments seek to oversee and leverage crowdsourcing; hence, they are interested in defining its scope and boundaries. For instance, the United States White House defines crowdsourcing as "a process in which individuals or organizations submit an open call for voluntary contributions from a large group of unknown individuals ("the crowd") or, in some cases, a bounded group of trusted individuals or experts."[4] The European Union report on crowdsourcing sees it as “the work of amateurs” and “a powerful political tool promoting democracy.”[5]

Given these varied interests and views, the efforts to better understand the landscape of crowdsourcing can be potentially valuable for broad audiences. Also, from the evolving definitions, the expansion of the concept of crowdsourcing is evident, whereby it originally started as a business activity and is now being viewed as a broader social activity. With this broadening, the scope and boundaries of crowdsourcing emerge as important social and organizational phenomena. Considering this expanded view, we provide an inclusive definition of crowdsourcing that integrates the diverse perspectives on crowdsourcing suggested by the evolving literature.

Definition: ***Crowdsourcing is an activity of obtaining value from a loosely organized group of people (crowd).***

This definition accounts for the diversity of the sponsors of crowdsourcing without the constraint that crowdsourcing must be sponsored by a for-profit organization. Indeed, crowdsourcing on a volunteer basis is common in science, and is often run by non-profit organizations. Second, the definition not only encompasses the provision of goods and services, including data, solutions and insights, but also includes the donation of money or computer time. Third, the definition accommodates both the typical cases where the crowds are beyond organizational boundaries and the situations where crowds are internal.

2.2. Prior taxonomies and frameworks of crowdsourcing

Over the years, researchers have articulated several different taxonomies and characteristics of crowdsourcing models. For example, Zhao & Zhu [10] classified crowdsourcing platforms into four groups based on their function: design and development, test and evaluation, idea and consultant, and others. Saxton et al. [25] identified nine different types of crowdsourcing models, including the intermediary model (e.g., Innocentive), citizen media production model (e.g., Current.com), collaborative software development model (e.g., FossFactory.org), digital goods sales model (e.g., iStock), product design model (e.g., Threadless), peer-to-peer social financing model (e.g., Kiva), consumers report model (e.g., AngiesList), knowledge-based building model (e.g., Wikipedia), and collaborative science project model (e.g., reCaptcha). Crowdsourcing contests (e.g., *Kaggle, InnoCentive*), idea platforms (e.g., *Dell IdeaStorm*), citizen science platforms (e.g., iSpot), and micro-task platforms (e.g., *Amazon's Mechanical Turk*) are a few other well-known platforms [26].

Estellés-Arolas and González-Ladrón-De-Guevara [7] identified eight main characteristics of crowdsourcing. These include a clearly defined crowd, a task with a clear goal, the recompense received by the crowd, the crowdsourcer, the benefits received, the participative nature of the task, the existence of an open call, and the use of the internet as a medium. Lukyanenko and Parsons [27] offer a taxonomy of crowdsourcing by focusing on the distinction between micro-tasks (e.g., Amazon's Mechanical Turk) and observational projects (e.g., eBird.org – a citizen science bird watching platform). There have also been efforts to categorize closely related activities. For example, Wiggins & Crowston [28] articulated a taxonomy of citizen science ranging from conservation projects to crowdsourcing projects.

Likewise, Lenart-Gansiniec [29] studied crowdsourcing in science and identified 12 distinct types, which range from crowd ideation and resource assembling to crowd decision-making and networking.

The analysis of crowdsourcing has begun to leverage automated literature review approaches [16]. Notably, Pavlidou et al. [30] conducted a literature review using quantitative content analysis (QCA), a technique that classifies parts of text to draw inferences about its content. QCA was applied to a relatively small corpus of 106 papers drawn from the crowdsourcing and crowdfunding literature. Among the key findings is the prevalence of the topic of innovation, the most frequent term following basic words such as crowd or crowdsourcing. This underscores the key value proposition of crowdsourcing – to support innovation. The second notable finding is the steady increase in the crowdsourcing literature from year to year. As the literature on crowdsourcing continues to expand, automated techniques can be easily scaled and leveraged to deepen our understanding of this phenomenon. Furthermore, the continued advances in natural language processing (exemplified most prominently by the use of large language models) present opportunities to discern complex patterns and draw deeper insights from the research on crowdsourcing [31]. Given this backdrop, we employ topic modeling, an unstructured machine learning approach, to identify topics latent in the research on crowdsourcing.

Despite the existing efforts to survey the literature and conceptualize crowdsourcing, we lack a comprehensive and theoretically grounded understanding of the different crowdsourcing models. First, there is considerable disagreement in the literature about the nature of different types of crowdsourcing and what constitutes a crowdsourcing project. Some scholars group several closely related areas - such as open-innovation and crowdfunding - under the umbrella of crowdsourcing, while others consider them different from crowdsourcing. For example, Zhao & Zhu [10] indicated differences between open-innovation and crowdsourcing systems. Second, many of the initiatives to understand crowdsourcing are more narrowly scoped, focusing, for example, only on one area of crowdsourcing, such as projects dealing with contests while ignoring others. Third, prior initiatives have not rigorously delineated the boundaries between the models. For example, they fail to consider the diversity of citizen science and treat it as a distinct crowdsourcing model. Indeed, many citizen science projects involve contests, observations, data analysis, problem identification, and generation – all distinct from but overlapping with other known models of crowdsourcing (e.g., micro-tasks, contests). Furthermore, not all citizen science involves crowdsourcing (for example, see [28]). Finally, many existing taxonomies for crowdsourcing systems focus exclusively on inter-system or intra-system perspectives, but not both. This limitation is significant because it fails to capture the complex and dynamic nature of crowdsourcing systems, which can only be understood by adopting a holistic approach that reflects the interplay between both perspectives.

As societal importance of crowdsourcing continues to increase, it is imperative that we understand the similarities and differences among various crowdsourcing system models and clearly identify their

[4] https://obamawhitehouse.archives.gov/blog/2014/12/02/designing-citizen-science-and-crowdsourcing-toolkit-federal-government

[5] https://op.europa.eu/en/publication-detail/-/publication/85558431-cfb4-4ff7-817d-5ad1338dc4b1

boundaries. To fulfill this goal, we used natural language processing (NLP) techniques to conduct a comprehensive review of the crowdsourcing literature without restricting our focus to a single type of crowdsourcing model (e.g., microtask) or specific domain (e.g., healthcare). Specifically, NLP was used to uncover hidden themes that constitute the conceptual foundations of scholarship on crowdsourcing in the IS and Business domains. We used the systems approach [20,22,21], encompassing both inter- and intra- systems perspectives, to allow distinct models to emerge organically and then conduct an in-depth examination of the research within each identified model. Therefore, this approach provides a more comprehensive and theoretically grounded framework (see Fig. 1) for understanding and managing crowdsourcing systems.

3. A systems approach to crowdsourcing

We adopt the theoretical lens of systems theory and sociotechnical perspectives to gain a deeper and more holistic understanding of crowdsourcing. We define a system as a collection of interacting or interrelated components that form a unified whole [20,32]. The *systems approach* focuses on studying the system as a whole, under the consideration of its components. Ackoff [20] elaborates on the systems approach as one that is "concerned with total-system performance even when a change in only one or a few of its parts is contemplated because there are some properties of systems that can only be treated adequately from a holistic point of view. These properties derive from the relationships between parts of systems: how the parts interact and fit together" (p. 661). A crowdsourcing model can be viewed as a system that consists of multiple stakeholders and their interactions. Therefore, a reductionistic approach that investigates its components in isolation may fail to capture insights that may be useful in our efforts to understand and manage the crowdsourcing phenomenon. Instead, a *science of design* (see [21]) that pays attention to the relationships between the parts, understands that optimizing the whole rather than the parts should be the goal of design, and uses a method of inquiry that goes beyond positivism and reductionistic thinking would be more fruitful in our endeavors to deepen our understanding of crowdsourcing and use it to benefit all stakeholders [21,22].

Benbya et al. [33] note that "digital technologies, in turn, foster new socio-technical systems such as wikis, social media, and platform ecosystems that are fundamentally changing the way people work and live" (p. 2). Crowdsourcing systems are a good example of this new form of social-technical ecosystems. It allows organizations and individuals to tap the crowd's wisdom beyond the traditional boundaries of organization, culture, and geography.

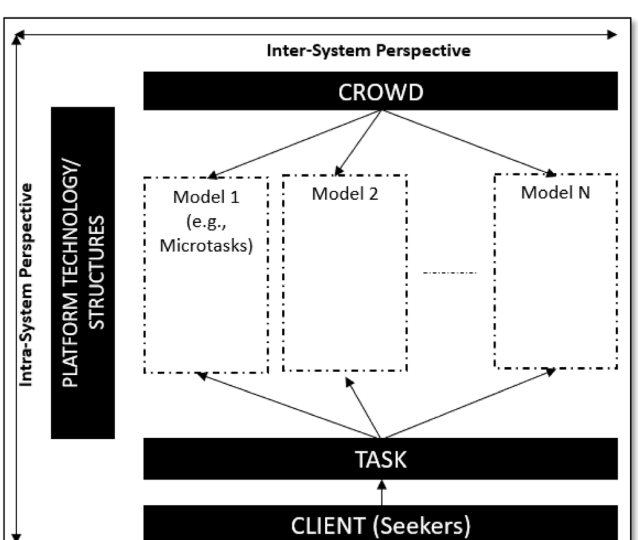

Fig. 1. Inter- and intra-system perspective of crowdsourcing system.

3.1. Social-technical components of a crowdsourcing system

Three stakeholders are primarily involved in a typical crowdsourcing system, namely, clients (seekers), the crowd, and the platform. Clients (e.g., organizations) seek solutions to problems (tasks). They connect with the crowdsourcing system by providing a task. The crowd consists of motivated individuals who help to solve a client's problems and are a critical component of the social system. Platform providers are intermediaries who facilitate the interaction between seekers and crowd solvers by providing digital platforms. Occasionally, organizations use their platform instead of third-party intermediaries (e.g., Dell IdeaStorm) and thus play the role of both seeker and platform provider.

Drawing on the conceptual foundations of social-technical systems (STS) [34] and based on the preceding discussions, we conceptualize crowdsourcing as a social-technical system consisting of social (e.g., crowd, client, and platform structures) and technical components (e.g., platform technology and task), and their interactions. Indeed, such a conceptualization is necessary to ensure that technical interests are not blindly pursued at the expense of the social aspects of crowdsourcing [21]. The technical component of the platform is referred to as platform technology, consisting of a platform interface including design features (e.g., discussion boards, leaderboards, online member profiles, task postings features), hardware, data sources, and other associative works. The social components of the platform are referred to as platform structures, such as fee structures, platform rules and regulations, policies, best practices, and other controls. "A fit /harmony/joint optimization between the technical and the social is expected to result in better instrumental outcomes (e.g., higher productivity) as well as humanistic outcomes (e.g., greater job satisfaction)." ([35], p. 698). Instrumental outcomes can vary across different crowdsourcing models, ranging from finding an innovative solution to a complex problem to collecting simple data. Humanistic outcomes include crowd motivation, job satisfaction, learning, and engagement. We refer to this conceptualization as an intra-system perspective.

Prior literature has identified some distinct crowdsourcing system models (e.g., micro-tasking models such as Amazon's Mechanical Turk). The nature of the task, the platform, and the crowd can differ in these distinct models. Our conceptualization of crowdsourcing systems acknowledges epistemological similarities across diverse models and helps to transfer problem-portable knowledge related to one model across distinct crowdsourcing models. We refer to this as an inter-system perspective. Fig. 1 depicts the inter-system and intra-system perspectives of a social-technical crowdsourcing system.

Guided by this conceptualization, we conducted a literature review to identify distinct crowdsourcing models as well as the research themes related to each model, the components within each system model, and their interrelationships.

4. Review methodology

Systematic literature review is a widely used method for reviewing the literature (e.g., see Lee et al. [36], Lei and Ngai [37], and Wu et al. [38]). However, Computational literature reviews, which rely on advanced technologies such as text mining/NLP, are fast becoming an alternative to systematic literature reviews [39] and have been proposed as a research frontier for information systems scholarship [16]. Prior research suggests that text mining techniques augment the capabilities of humans and provide broader and deeper insights than would be possible with humans alone. Manual reviews require an upfront investment in time and effort, which can be enormous as the corpus grows [40].

We integrated text analytics with human perspectives for a balanced and comprehensive literature review. Our study employed topic modeling, an unsupervised machine learning technique, to identify key themes in a collection of crowdsourcing abstracts from selected journals. Beyond efficiently handling large volumes of data, the incorporation of text analytics provides a more systematic approach that mitigates certain human biases. Automated techniques assist in uncovering patterns objectively, complementing and enhancing human analysis. Specifically, we used a traditional probabilistic model called Latent Dirichlet Allocation (LDA), Non-Negative Matrix Factorization (NMF), and a recent advanced approach that uses embeddings from Bidirectional Encoder Representations from Transformers (BERT) to extract topics latent in the corpus related to crowdsourcing.

Our broad strategy for synthesizing the results of multiple topic models is to leverage their respective strengths and consider the limitations to ensure the overall conclusions are holistic and balanced. This strategy has been successfully employed in other research that used natural language processing techniques. (see Larsen & Bong [41]).

First, by synthesizing the results from multiple models we are able to enhance the topic coherence and interpretation, as it allows researchers to strike a balance between broader themes identified by LDA and more granular sub-topics unraveled by NMF. Furthermore, it can reconcile the limitations inherent in each approach. For instance, LDA and NMF, which require a priori specification of the number of topics, start with a bag-of-words that neglects context, while BERTopic does not require one to specify the number of topics and reflects contextual information by using embeddings that capture the rich semantic relationships between words [42].

Second, algorithmic diversity allows for identifying a broader set of perspectives while overcoming their shortcomings. LDA's strong foundation in statistics and probability, NMF's anchoring in matrix factorization, and BERTopic's ability to leverage state-of-the-art embeddings together provide consistent and interpretable topics.

Although these approaches are fairly advanced, they require humans with domain knowledge to validate and interpret the results [43]. Finally, we used insights from the synthesized topics and knowledge about our domain to further validate the results by an algorithm called Correlation Extraction (CorEx). Unlike other topic modeling approaches, CorEx is not constrained by assumptions and can reveal domain-relevant themes that may be missed by approaches such as LDA and NMF [19]. As Gallagher et al. [[19], p. 530] note, "Topic models are often susceptible to portraying only dominant themes of documents. Injecting a topic model, such as CorEx, with domain knowledge can help guide it towards otherwise underrepresented topics that are of importance to the user." Thus, our study synthesizes the outputs of several topic models and incorporates domain-specific "anchor words" guided by our theoretical framework to identify relevant themes. Table 1 shows the steps we followed.

Prior researchers have employed various data samples to understand academic literature, ranging from analyzing simple author-provided keywords to thoroughly examining complete journal articles. For example, Jeyaraj and Zadeh [46] focused specifically on author-supplied keywords in the Basket of Eight journals, allowing them to effectively evaluate the landscape of the IS field. It is common for IS researchers to analyze article abstracts since they capture the essence of the full-text [15,47]. For instance, Sidorova et al. [48] analyzed the abstracts of three leading IS journals and provided valuable insights into the intellectual core of the IS domain. In general, abstracts succinctly represent the gist of the articles and are a good approximation of the topics underlying a domain. Thus, we believe that abstract analysis yields a robust set of topics.

For collecting the data used in this study, we performed a keyword search using relevant search terms[6] to extract abstracts of articles from a list of selected journals indexed in the Scopus database. In addition to reviewing relevant prior literature, we considered experts' opinions to develop a comprehensive list of search terms. It must be noted that crowdfunding, which focuses on raising money from many people (crowd) to fund projects, is different from other crowdsourcing systems that require the crowd to share their time or skills. Therefore, crowdfunding was excluded from our study. We selected a list of key IS journals and premier business journals as our pool. To create a list of mainstream IS journals, we selected information management journals with ratings of 3 or higher in the academic journal guide published by

Table 1
Review approach (adapted from [44] and [45]).

1) Review plan	Based on the objectives outlined in the introduction, we developed initial criteria for the inclusion and exclusion of articles. Our plan and the framework were iteratively further developed as we moved on and identified subsequent important issues.
2) Literature identification	**Search:** We selected top IS as well as premiere business journals matching our objectives. • IS journals with ratings of 3 or higher in the academic journal guide published by the Chartered Association of Business Schools (CABS) • The proceedings from the International Conference on Information Systems (ICIS) • The Financial Times top 50 business journals and CABS journals with 4 and 4*ratings. Our final list consists of 140 journals and one conference proceeding. Our search was limited to abstracts, titles, and author keywords of articles published in these journals.**Selection:** We used a list of relevant keywords. The initial search yielded 421 articles. After removing abstracts of unrelated articles, retracted articles, and articles without abstracts, our final sample consisted of 410 abstracts published from Jan 2007 to May 2022.**Quality assessment:** Since we only included renowned journals, we infer that the published papers are of an acceptable quality for inclusion. We also deemed this sufficient because of the critical nature of our review [44].
3) Data extraction and categorization	We used topic modeling to categorize the papers and to identify key themes/topics. Authors carefully reviewed the key articles for each theme/topic. Ambiguity was resolved via discussions of all authors [44]. The topic modeling process involves four main steps: • Abstract pre-processing: pre-processed abstract data (e.g., remove stop words, lemmatize text) to reduce inheritance noise. • Topic Identification: performed Latent Dirichlet Allocation (LDA), Non-Negative Matrix Factorization (NMF), and BERTopic on preprocessed data to identify key themes. • Topic labeling and Synthesizing: Authors compared topics generated by each method, then synthesized and labeled them. • Validation: validated the results using a semi-supervised topic modeling approach, Anchored Correlation Explanation (Cor-Ex), and manually evaluated key articles contributing to each topic.
4) Critical analysis	We leverage the suggestions of problematization by Alvesson & Sandberg [14] to identify distinct crowdsourcing models, research themes related to each model, components within each system model, and their interrelationships. Specifically, we adopted the conceptual foundations of social-technical systems (STS) [34] to conceptualize the crowdsourcing system as a social-technical system consisting of social components (e.g., crowd, client, and platform structures) and technical components (e.g., platform technology and task), and their interactions.

[6] (crowdsourc* OR crowdwork* OR crowd-sourc* OR "crowd work" OR (crowd AND contest) OR (crowd and "open innovation")) and their meaningful combinations AND NOT (crowdfund* OR "crowd out")

the Chartered Association of Business Schools (CABS). This list includes all eight journals in the Senior IS Scholars' Basket of Journals.[7] To capture emerging topics, we added the proceedings from the International Conference on Information Systems (ICIS), a premier conference in IS. We also added premier business journals to the list to make our study comprehensive, as other business disciplines also actively pursue research on crowdsourcing. The premier business journals included were the Financial Times' top 50 business journals and CABS journals with 4 and 4* ratings. Our final list consists of 140 journals and one conference proceeding – making it the largest corpus of articles on crowdsourcing to our knowledge. Our search was limited to abstracts, titles, and author keywords of articles published in these journals. The initial search yielded 421 articles. After removing abstracts of unrelated articles, retracted articles, and articles without abstracts, our final sample consisted of 410 abstracts published from Jan 2007 to May 2022. Since the term "crowdsourcing" was first introduced in an article by Howe [23], we limited our search to articles published after 2006 to ensure consistency in what is widely regarded as crowdsourcing.

The number of publications shows an upward trend. We counted the citations based on the country of the corresponding authors. The majority of publications originate from the United States, followed by the United Kingdom, Germany, and China. Regarding publication outlets, ICIS is the leading source, followed by journals such as *Computers in Human Behavior* and *Expert Systems with Applications*. See Figs. A1–A3 in Appendix A for more information. The mean word count of abstracts was 189 with a standard deviation of 58.

Following prior research (e.g., Dantu et al.[15]), we preprocessed data by converting text to lowercase and removing punctuations, numbers, and stopwords (e.g., "the", "a", "is", "of") to reduce the inherent noise in the data. We then lemmatized the text to reduce words to their base/root dictionary form. Fig. 2 shows a word cloud of the corpus.

4.1. Topic modeling with LDA and NMF

Our first analysis is based on Latent Dirichlet Allocation (LDA). LDA is a popular algorithm for topic modeling. It has been widely used to

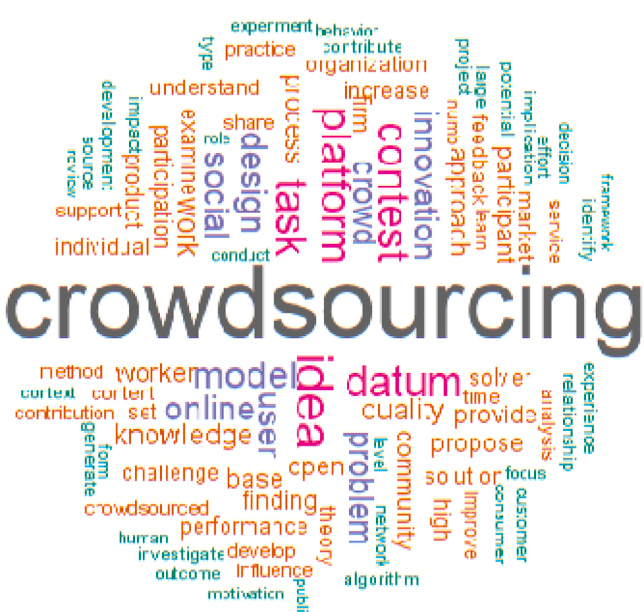

Fig. 2. Word cloud of the corpus.

extract topics from large corpora (e.g., [15]). LDA is a suitable algorithm when documents represent multiple topics [17]. The algorithm requires a preselected number of topics k as an input parameter. It is a generative process that begins with randomly assigning each word in each document to one of the k topics. Based on the probability distribution of topics across the words and the proportion of topics for each document, LDA iteratively assigns weights to each document-word-topic [15].

Before running LDA, selecting a suitable value for the number of topics (k) is essential. A larger value could lead to redundant and/or uninterpretable results, while a smaller number could conflate otherwise distinct topics. We used a robust combination of a minimization algorithm [49] and a maximization algorithm [50] to identify the optimum number of topics k. These are from the ldatuning package in R, which has been previously used in recent papers [51]. According to the "Griffiths2004" metric, high scores indicate a greater frequency of terms appearing together within a topic, enhancing the clarity and understandability of topics. Conversely, the "CaoJuan 2009″ metric considers both intra-cluster (within topic) and inter-cluster (across-topic) similarity, aiming for minimal inter-cluster density to ensure topic stability. This implies that lower inter-cluster density leads to more distinct and interpretable topics. Both algorithms identified the optimum number of topics as 18 – a common number when using LDA (see Fig. 3).

Therefore, we extracted 18 topics using the LDA algorithm implemented in the R topicmodels package.[8] The input to LDA is a document-term matrix, where each document is a vector of frequencies across the entire vocabulary of the corpus. This method uses a bag-of-words, which disregards word order but captures essential frequency information for topic modeling. Through Gibbs sampling, the LDA algorithm iteratively assigns words to topics based on their probability of occurrence within documents, uncovering latent topic structures. Fig. 4 shows the top 10 terms in each topic.

Table 2 shows these topics and the 20 most frequent terms for each topic. Two authors with more than ten years of research experience in crowdsourcing manually evaluated these 18 topics and grouped them into themes with appropriate labels based on the key papers that were associated with each topic. Additionally, a sample of top articles within each category was manually evaluated. We identified five broad crowdsourcing systems themes from the literature: 1) crowdsourcing contests systems; 2) micro-tasking systems; 3) idea generation systems; 4) crowdsourcing systems for data collection; and 5) other crowd-based

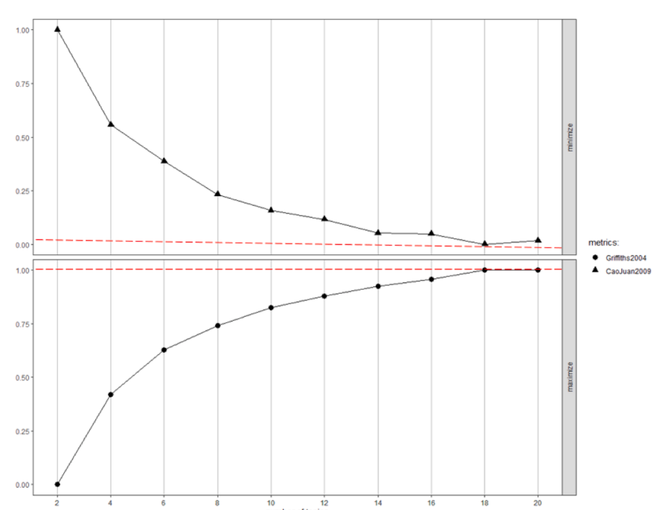

Fig. 3. Optimal number of topics.

[7] https://aisnet.org/page/SeniorScholarBasket

[8] https://cran.r-project.org/web/packages/topicmodels/topicmodels.pdf

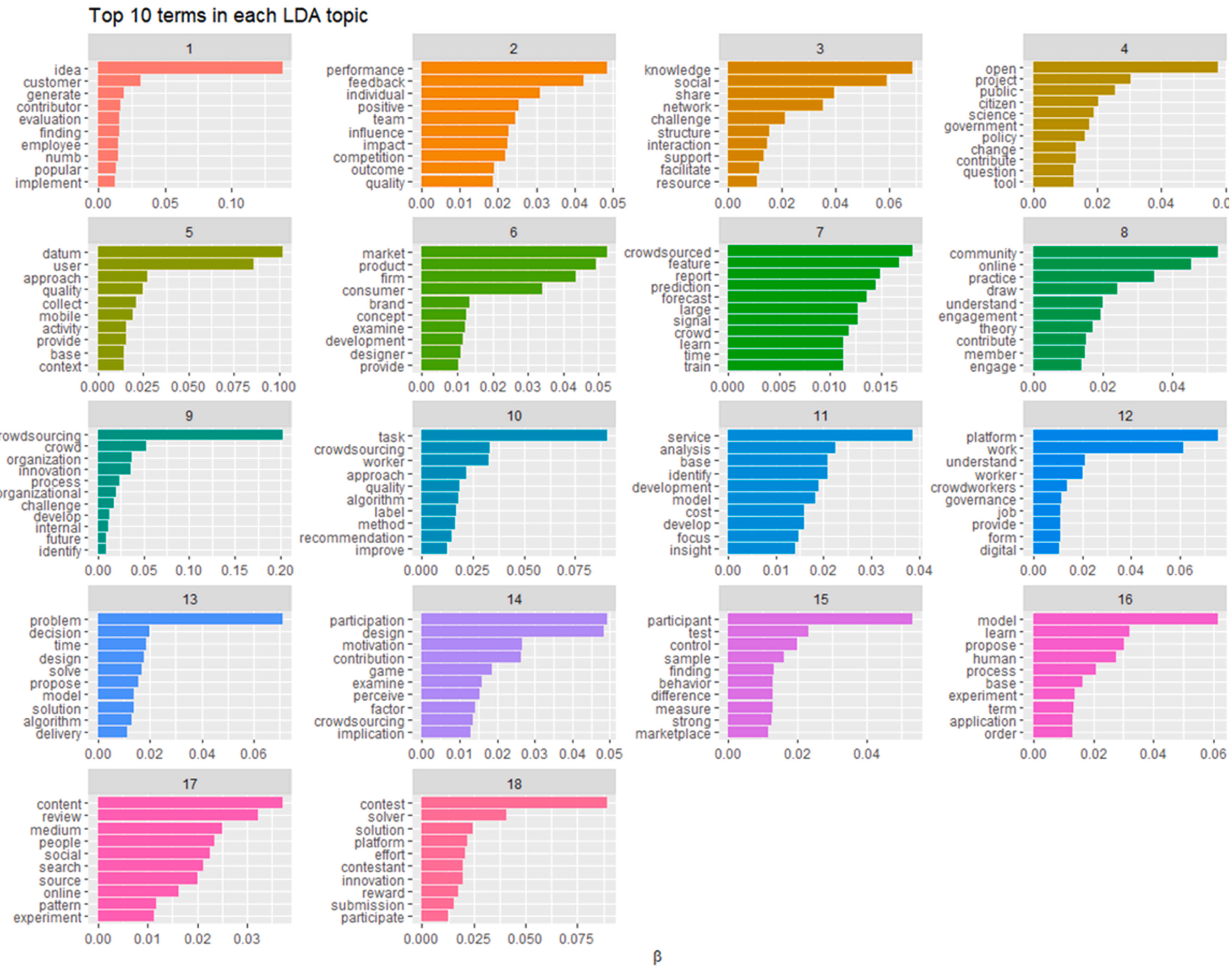

Fig. 4. Top 10 Terms in each topic.

collaborative networks communities. Results confirm that prior research mainly focused on perspectives of different system components, namely, the clients, the platforms, and the solvers from the crowd, without considering the interplay among them. We contend that viewing these perspectives as a whole can lead to a richer understanding of crowdsourcing.

To test the robustness and consistency of the topics obtained using LDA, we used NMF to extract and evaluate the topics. NMF's sparseness of representation [52] and the constraint of non-negativity generally help identify the essential words belonging to a topic, thus making the topics more interpretable. They are also computationally efficient compared to LDA. For example, Egger and Yu [[42], p. 6] found "…. that the results obtained from NMF are more in line with human judgment, thereby outperforming LDA in general." Based on the coherence value, the optimal number of topics with NMF was also identified as 18. As shown in Table A1, the results are consistent with the topics obtained using LDA.

4.2. Topic modeling with BERTopic

The input to LDA is a document-term matrix, the columns of which are essentially a bag-of-words that fail to capture contextual information about the words. Recent models based on the transformer architecture [53] provide embeddings (i.e., a vector of scores representing latent dimensions) that are semantically richer than the bag-of-words, as they were trained on a large corpus. The embeddings obtained from pre-trained models such as Google's BERT have yielded remarkable results in NLP tasks such as question and answer inference, text classification, and text summarization (e.g., [54]). The transformer architecture is the basis for the spectacular popularity of large-language models such as ChatGPT from OpenAI [55]. To validate the topics obtained by LDA and to draw additional insights, we used BERTopic, a recently developed approach that uses BERT as the starting point for extracting topics from a corpus [18].

BERTopic leverages pre-trained transformer models such as BERT (e.g., "bert-base-uncased") to generate contextualized word embeddings. BERTopic first obtains the embeddings for the raw documents and then reduces the dimensionality of the embedding vectors using UMAP (Uniform Manifold Approximation and Projection), a dimensionality reduction method widely used for visualization. The reduced dimensions are then used by HDBSCAN ("Hierarchical Density-Based Spatial Clustering of Applications with Noise") to generate clusters.[9] HDBSCAN does not require the researcher to specify the number of topics ahead of time. The clusters thus obtained are the topics of interest, and the words most pertinent to each topic are obtained by performing TF-IDF vectorization on the documents belonging to each cluster. The seven topics identified by BERTopic (see Table 3) were similar to the

[9] See https://hdbscan.readthedocs.io/en/latest/how_hdbscan_works.html

Table 2
LDA topic analysis.

Topic ID	Key Words	Main theme
Inter-system perspective (Crowdsourcing system models)		
V1	idea customer generate contributor evaluation finding employee numb popular implement cognitive support implementation individual generation ideation crowdsourced company diverse convergence	**Idea generation**
V18	contest solver solution platform effort contestant innovation reward submission participate numb prior agent increase experience seeker examine relationship win implication	**Crowdsourcing contests**
V5	datum user approach quality collect mobile activity provide base context demonstrate rate analyze field investigate set setting content collection experience	**Crowdsourcing for data collection** • Crowd-based forecast and crowd sensing (e.g., mobile sensing to collect real-time traffic data) • Surveys
V15	participant test control sample finding behavior difference measure strong marketplace intention support survey negative researcher reduce belief filter hypothesis online	
V7	crowdsourced feature report prediction forecast large signal crowd learn time train achieve position return accuracy accurate map initial apply expert	
V12	platform work understand worker crowdworkers governance job provide form digital experience crowdwork conduct offer career pay phenomenon creative relationship explore	**Micro-tasking** • Crowdwork • Crowd-based labeling and classification
V10	task crowdsourcing worker approach quality algorithm label method recommendation improve group exist classification estimate set perform allocation characteristic reliability judgment	
V4	open project public citizen science government policy change contribute question tool aim management form production framework technology face software collaborative	**Other crowd-based collaborative network communities** • Wikipedia; social-learning networks; social media for disaster management; • Co-creation; user-generated content
V17	content review medium people social search source online pattern experiment integrate site discussion create web behavior common factor post preference	• Citizen science & disaster management
Intra-system perspective (Crowdsourcing stakeholders perspectives)		
V2	performance feedback individual positive team influence impact competition outcome quality negative investigate increase online positively high tournament provide receive addition	**Platform perspective***Platform technology:* • Feedback • Solution evaluation mechanism • Role as IT service provider*Platform structures:* • Model; platform governance and controls
V13	problem decision time design solve propose model solution algorithm delivery dynamic condition environment approach cost introduce optimal analysis choice vehicle	• Provider trust
V16	model learn propose human process base experiment term application order set include dataset annotation distribute method topic class build error	
V11	service analysis base identify development model cost develop focus insight capability emerge issue provider trust role future mechanism area digital	
V3	knowledge social share network challenge structure interaction support facilitate resource business strategy technology enable innovative create case distance virtual opportunity	**Crowd/ Solver perspective** • Knowledge sharing in crowdsourcing (e.g., willingness to share knowledge; knowledge sharing patterns) • User motivation and engagement (e.g., gamification; extrinsic and intrinsic motivations)
V8	community online practice draw understand engagement theory contribute member engage source boundary argue company activity perspective group identification professional field	
V14	participation design motivation contribution game examine perceive factor crowdsourcing implication lead context intrinsic discuss increase relationship autonomy concern gamification player	
V6	market product firm consumer brand concept examine development designer provide benefit business high good increase lead promise time unique access	**Organization/ Client/ Seeker perspective** • Internal crowdsourcing; organizational role • Organizational motivations, challenges; intentions to crowdsource
V9	crowdsourcing crowd organization innovation process organizational challenge develop internal future identify framework large intermediary outcome year external conceptual increasingly insight	

main themes identified based on the LDA topic model. Specifically, the same five crowdsourcing models were reflected in Topics 2 to 6. Topic 0 in BERTopic consists of general words that do not form any cohesive topics. In our case, the words were mostly related to organizational and solvers perspectives. Similarly, Topic 1 was also a less coherent topic representing a wider area of research involving platform and task perspectives.

We also plot inter-topic distance to see how close these topics are to each other (see Fig. 5). Each circle represents a topic, and its size is the frequency of the topic across all the documents.

Fig. 6 shows how the topics have evolved over time. As can be seen from Figs. 5 and 6, crowdsourcing contests and idea generation (topics 2 and 3) are among the most researched crowdsourcing models in the IS and business domains. Micro-tasking and other crowd-based collaborative networks follow this. There is not much research on crowdsourcing for data collection; however, the topics have recently shown an increasing trend, as can be seen in Fig. 6.

4.3. Anchored correlation explanation (CorEx) topic modeling

Anchored CorEx is a topic modeling approach that allows researchers to provide words that can nudge the topics in a desired direction. The words identified by LDA, NMF, and BERTopic, which were described in the previous section, were used to guide the extraction of topics by anchored CorEx [19]. Specifically, we explored anchor words “contest,” “idea,” “crowdwork,” “label,” “datum,” and “citizen”— and obtained keywords related to crowdsourcing models presented in Table 4. Topic 0 shows terms related to the crowdsourcing contest model, such as prize

Table 3
BERT topic analysis.

Topic	Keywords	Theme
0	crowdsourcing 0.09 innovation 0.042 organization 0.035 crowd 0.031 firm 0.031 organizational 0.03 design 0.029 process 0.028 knowledge 0.024 internal 0.024	Organization/Solver Perspective
1	task 0.057 algorithm 0.051 worker 0.046 propose 0.04 problem 0.039 label 0.039 crowdsourcing 0.032 approach 0.032 method 0.029 model 0.028	Platform/task Perspective • Task assignments, Algorithms
2	idea 0.107 product 0.066 consumer 0.042 customer 0.041 user 0.035 brand 0.031 community 0.03 generate 0.029 market 0.028 convergence 0.024	**Idea generation**
3	contest 0.139 contestant 0.059 solver 0.058 crowdsourcing 0.049 solution 0.047 submission 0.043 performance 0.038 platform 0.036 team 0.034 effort 0.034	**Crowdsourcing contests**
4	work 0.123 worker 0.083 crowdworkers 0.06 platform 0.056 crowdwork 0.053 career 0.043 job 0.041 autonomy 0.038 crowdsourcing 0.03 crowdworking 0.028	**Micro-tasking**
5	open 0.058 government 0.057 citizen 0.056 public 0.048 social 0.043 datum 0.042 innovation 0.036 sector 0.035 content 0.034 source 0.032	**Other crowd-based collaborative network communities** • Citizen science • user-generated content
6	datum 0.138 collection 0.063 sample 0.057 ocm 0.052 quality 0.038 crowdsourcing 0.037 participant 0.036 nonus 0.036 difference 0.033 judgment 0.033	**Crowdsourcing for data collection**

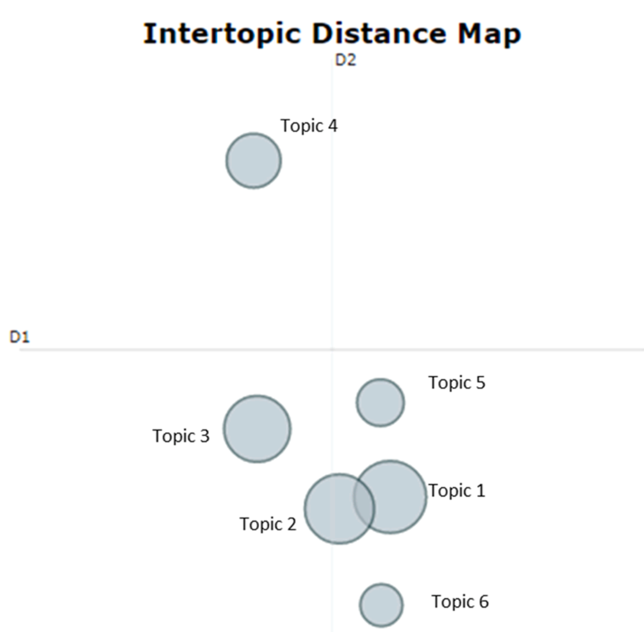

Fig. 5. Inter-topic distance map.

money, performance, and winners, while Topic 1 shows terms related to idea generation, such as innovations and new product development. Topic 2 represents research themes associated with crowd workers, such as compensation, growth, and ability. Topic 3 comprises keywords related to types of micro tasks such as labeling, annotations, and classifications. These two topics together represent the micro-tasking model. Topic 4 includes terms related to data collection, analysis, and validation. Finally, Topic 5 represents other crowd-based communities such as user-generated content and citizen science.

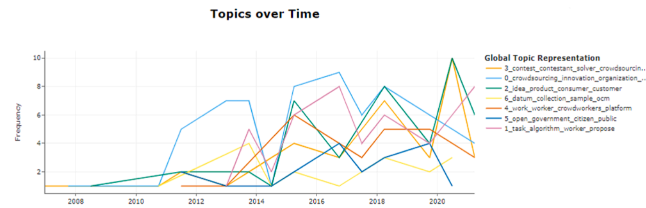

Fig. 6. Topics over time.

Table 4
Anchored CorEx topic analysis.

Topic	Keywords	Theme
0	contest, contestant, win, prize, solver, solution, host, performance, seeker, increase	**Crowdsourcing contests**
1	idea, generate, ideation, product, innovative, generation, ideators, initiative, operationalize, raw	**Idea generation**
2	crowdwork, predictor, consideration, country, crowdworkers, compensation, growth, ability, fruitful, dissemination	**Micro-tasking**
3	label, annotation, metric, expensive, reliability, minimize, efficient, paradigm, limitation, classifier	
4	datum, collect, analysis, analyze, adaptive, analytics, validate, rank, automatic, panel	**Crowdsourcing for data collection**
5	citizen, science, public, ugc, project, smart, engage, company, political, efficiency	**Other crowd-based collaborative network communities**

As presented in Table 2, we identified and grouped themes into two main categories: inter-system and intra-system perspectives. The following section discusses the results of topic modeling in detail.

5. Analysis results

Based on the results of the topic analysis, we have identified different types of crowdsourcing systems models from the main stakeholders' perspectives. Sections 5.1 and 5.2 discuss these systems models and the nature of components/stakeholders involved in each model. Section 5.3 maps the key themes of crowdsourcing models and the stakeholders involved and presents the sample research articles for each topic from the literature. The section also presents the research gaps revealed by our analysis.

5.1. *Inter-system perspective: types of crowdsourcing system models*

We have identified five main types of crowdsourcing systems. When reviewing the key papers in each theme, we identified some overlap between crowdsourcing for data collection and crowd-based collaborative network communities. Additionally, as per hierarchical topic modeling, out of the five distinct models identified, crowdsourcing for data collection and other crowd-based collaborative models - such as citizen science - show a close association (see Fig. 7). Hence, we grouped these overlapping themes and ended up with four main types of

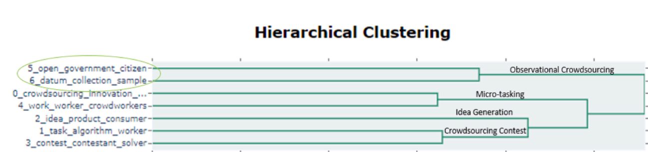

Fig. 7. Hierarchical clustering with BERT.

crowdsourcing systems. Following Lukyanenko and Parsons [27], we called it "observational crowdsourcing."

There are key differences among the four types in terms of task characteristics, solver motivations, and platform structure (e.g., incentive mechanisms). Even though we have identified distinct boundaries, it is important to understand that some systems can have characteristics of more than one type. The following section will discuss each of the four main specified types of crowdsourcing systems.

1) Contest model

The contest model is the most widely investigated area in the crowdsourcing literature in our corpus [56,57]. In a typical crowdsourcing contest, a solver who submits the best solution will be entitled to a monetary reward. Thus, the competition among individual solvers and/or solver teams is a key feature of this model. This model shows features of all-pay auctions and tournaments. Segev [58] provides a review of the literature related to crowdsourcing contest models. Crowdsourcing contests have been used in several domains, including data science (e.g., Kaggle), software development (e.g., Top Coders), healthcare (e.g., CrowdMed), and research & development (e.g., Innocentive).

Several scholars have investigated the impact of different factors such as competition intensity, interim performance feedback (public and/or private), reward structure, discussion forums, solver characteristics, and crowd size on contest outcomes such as solver effort, performance, and solution quality. For example, Dissanayake, Mehta, et al. [59] demonstrated that solvers' self-efficacy positively influences their effort and ultimate performance in a competitive contest setting, while it has a negative impact on effort in non-competitive settings.

Performance feedback is another important factor in the crowdsourcing contest model. Feedback can take many different forms. For instance, public or private feedback may involve detailed comments or relative performance (ranking). Jian et al. [2] showed that in-process feedback generally increases the volume of the submissions. However, extremely negative or highly positive feedback discourages overall submissions. A different study [56] showed that solvers strategically alter their efforts to maximize their utility in light of interim relative performance feedback. Mihm and Schlapp [60] argued that the decision to provide feedback should be based on whether a seeker wants to enhance the quality of average performance or to obtain the best solution. Private feedback is the best choice in an innovation contest where the seeker looks to optimize the quality of the best solution. On the other hand, public feedback is suitable when there is not much performance uncertainty. Feedback encourages solver effort and engagement [61]. Lee et al. [62] investigated the impact of platform feedback and systematic bias of workers on the crowdsourcing contest outcome.

Crowdsourcing contest platforms are mainly competitive. Many of these platforms use gamification elements (e.g., leaderboard, medals) to intensify the competition among the solvers and enhance solver motivations. Interestingly some crowdsourcing contest platforms facilitate collaboration among rival teams through forums and other means of knowledge-sharing (e.g., Kaggle). In addition to winning the reward, learning is another key motivation behind participation in these contests, particularly those involving knowledge-intensive tasks. Knowledge-sharing behaviors in such a setting could be reciprocal and enhance their ultimate performance [63]. The effectiveness of shared knowledge depends on factors such as volume, quality, and generativity [57]. Participating in contests with superstars is beneficial in the long run due to the learning effect [64].

In the contest model, the competition is mainly induced through a reward structure. A proper incentive structure is important for attracting solvers and enhancing their motivations. High rewards result in more submissions and more high-quality solutions than low rewards (T. X. [65]). The amount of monetary reward and the number of rewards impact the solver's level of effort. Some scholars showed that, under certain assumptions, winner-takes-all is the optimal reward structure [58]. However, this is still an ongoing debate in the field.

Despite their benefits, contest models have notable limitations. First, relying on altruistic motives may not be as effective as in other models, especially in the observational one. This means that to be effective, often substantial monetary incentives must be provided to the contest participants. Second, peer-to-peer learning – a common draw for crowds to participate in crowdsourcing - may be limited, especially in contests with high levels of participant competition (e.g., [57]). Third, contest models do not appear to be well-suited for longitudinal tasks (e.g., monitoring local air pollution over time) (J. [66]). These limitations, however, offer opportunities for future research on mitigating these shortcomings. For example, an interesting open area of research is the development of platforms for longitudinal contests. Another notable opportunity is the integration of contests into other crowdsourcing models, such as the observational model. This way, some of the limitations of contest models (such as their unique motivational structure), may be mitigated by leveraging the motivational structures that have been effective in other models.

Prior studies have mainly investigated the individual impacts of numerous features (e.g., type of feedback, gamification elements, collaboration elements, and reward structure) on contest outcomes. However, we contend that the features are interdependent and, therefore, crowdsourcing must be viewed holistically (i.e., as a system). Investigating the effect of individual features in isolation may not give an accurate picture of the overall performance outcomes of the system.

2) Micro-tasking model (crowdwork platforms)

Micro-tasking crowdsourcing is defined as "a type of online, participative activity in which undefined, generally large groups of individuals take on micro-tasks posted on a web-based, third-party platform in an open call by organizations or individuals in exchange for micropayment" ([67], p. 281). Micro-tasking platforms such as Amazon Mechanical Turk (MTurk), MobileWorks, and Figure Eight (formerly Crowdflower) fall into this category [67]. On these platforms, "crowd workers perform simplistic and repetitive tasks, such as classifying images, for which they earn a couple of cents" ([68], p. 68). In addition to the difference in task characteristics, workers in these platforms make a substantial part of their income through crowd work compared to participants in other crowdsourcing models [68].

Much of the research on micro-tasking has been conducted from the workers' perspective. Early research argued that these platforms have the potential for both worker empowerment and exploitation [69]. Workers in these platforms expect to satisfy several needs, including "relatedness (connectedness and societal impact), existence (income, basic rights, and rewarding experience), and growth needs (impact on self and skill development)" ([70] p. 1). In a similar study, Kost et al. [71] identified reward, self-improvement, moral, and social motives as four main sources that make these micro-tasks meaningful for crowd workers. A survey conducted on the MTurk platform showed that crowd workers value access, autonomy, fairness, transparency, communication, security, accountability, impact, and dignity [67]. At the same time, crowd workers have raised concerns about fairness, communication, security, and accountability. Examples include unfair payments, scamming, and irresponsible/unethical behaviors by the seekers [67].

Scholars have investigated ethics and fairness in crowdsourcing practices. In some sense, microtask platforms are considered ethically problematic. Schlagwein et al. [72] identified five emerging ethical norms in micro-task crowdsourcing: payment fairness, openness and feedback transparency, opportunities based on achievement and talents, and work that is free from temporal and spatial restrictions. Brawley & Pury [73] investigated job experience in MTurk, including job satisfaction, information sharing, and worker turnover. They found that unfair wages and inaccurate time requirements mentioned by the seekers are two main factors leading to job dissatisfaction and, consequently, worker turnover.

Crowdwork is characterized by highly decomposed, repetitive, and rigid tasks under low wages. These characteristics negatively impact workers' psychological bond with the task [4,68] and could be a plausible reason for high worker dissatisfaction and turnover. Ma et al. [74] showed that crowd workers are self-organized into independent online communities (e.g., TurkerNation) to derive greater meaning from their work. Active participation in these online support communities mitigates workers' intentions to quit.

Researchers are also using these micro-tasking platforms to conduct surveys. This area has some overlap with crowdsourcing for data collection. Several scholars have explored the impact of using these micro-tasking platforms for survey data collection. First, satisficing behavior of workers in these low-paying environments reduces their attention, thereby adversely affecting the validity and quality of their responses. Therefore, a better filtering mechanism is required to exclude the responses from low-attention workers [75]. Second, researchers must be mindful of where the data come from when they use global platforms to collect data. For example, Steelman et al. [76] identified unexplained differences in data from US-based and non-US-based samples. Finally, researchers suggested that MTurk data are more suitable for generalizing studies with diverse cognition than contextualizing studies [77].

The workers in multitasking platforms vary in levels of expertise and skills, and thus the quality of task completion. Verifying submitted answers is costly and time-consuming (J. [78]). Therefore, data quality is a vital issue in these platforms and demands more research. Wang et al. [78] proposed heuristics-based dynamic allocation strategies to enhance labeling data quality.

A notable limitation of the micro-task model is the difficulty in supporting continuous, longitudinal projects. For example, it may be challenging to ensure this in cases where the same participants are needed to collect data at different moments in time (e.g., for multi-stage study designs). There is generally a high level of attrition and transience among the workers on these platforms (partially related to motivational and low payment issues). Therefore, ensuring that the same cohort of users would participate in multiple related and interdependent tasks is a significant challenge, and, consequently, presents a corresponding research opportunity.

Another notable limitation of micro-task model is what we call "one-way street integration" with other crowdsourcing models. Specifically, micro-tasks are occasionally used to supplement the processes within other crowdsourcing models [79]. For example, an ideation platform may use Amazon's mechanical Turk for prescreening of the idea submissions. In these scenarios, micro-tasking is used to supplement other crowdsourcing models. However, the reverse, that is, the use of other crowdsourcing models to supplement micro-tasking remains elusive, raising a question of how to leverage other crowdsourcing models to support micro-tasking. One potential benefit of doing so may be in mitigating some of the shortcomings of micro-tasking, such as high attrition rates and low motivation of the crowds, which could be supplemented if there is an effective two-way integration with other crowdsourcing models in which crowds are more engaged.

Finally, while our review identified several common limitations with micro-tasking systems, such as worker dissatisfaction, lack of motivation, lack of worker protection, and low-quality work, among others, we note an important caveat about these findings. Many studies in this area are based solely on MTurk; therefore, more studies need to be conducted on different micro-tasking platforms to generalize these findings.

3) Idea generation model (idea markets)

Early crowdsourcing systems mainly developed around *idea markets* where "consumers can post new product ideas that are voted by their peers" ([80], p. 2138). Researchers have shown that consumers often prefer to buy products from user-driven rather than designer-driven firms. Moreover, fully open participation of users rather than selective participation has a much stronger impact on their attitude toward products [81]. Huang et al. [80] noted that novel concepts initially inundate the idea markets and diminish over time, while the average of potential ideas increases as consumers learn more about the system. Bayus [82] found that the likelihood of a significantly different idea replacing a previously implemented consumer idea is less in these idea markets.

Furthermore, the likelihood of idea implementation depends on several characteristics, such as user experience, idea presentation, and feedback valence (Q. [83]). The crowd generally generates better ideas in terms of novelty and customer benefit; however, they may not always be feasible [84]. Hwang et al. [85] showed that participation in customer-support communities enhances the crowd's ability to generate creative ideas.

Another stream of research in this category focuses on an idea evaluation process. Some crowdsourcing platforms use the same crowd to generate and evaluate ideas (e.g., peer voting), while others may use expertise and/or peer voting to evaluate ideas. The preference market (idea evaluation as a choice task) and rating scale (idea evaluation as a judgment task) are popular methods for evaluating ideas. Blohm et al. [86] showed a perceptual difference between these two mechanisms, and the rating scale-based tasks show higher ease of use than preference market-based tasks. Moreover, idea readability and task variability moderate the relationship between perceived ease of use and users' decision quality. Ideas and sentiments of their comments also influence the number of votes the ideas receive [87].

An active research stream has focused on unraveling participant motivations. Leimeister et al. [88] identified several motives behind user participation in ideation platforms, such as learning, direct compensation, self-marketing, and social motives. When an idea is not selected for implementation, the contributor's willingness to contribute ideas in the future could be negatively impacted. Organizations can provide an explanation for the rejection to mitigate such adverse effects [89]. This becomes especially important when an algorithm performs the selection.

There are a few studies related to feedback in ideation projects. Wooten & Ulrich [90] showed that directed consumer feedback positively correlates with the number of idea submissions and the average quality of submissions, while random or no feedback may enhance the quality of top-end submissions. In addition, directed feedback is positively associated with solver participation. Koh [91] studied the effect of providing solution exemplars to the participants. The study found that prizes and characteristics of exemplars influence their adoption by the participants and, in turn, improve the effectiveness of ideas. Our review suggests that not many studies are directly related to the idea platform policies, ethics, and best practices. Moreover, there is still room for improvement in the idea evaluation and filtering process.

As our review suggests, there are notable limitations to the idea markets. First, if the crowds are unfamiliar with the domain of interest (such as healthcare, science, and specific engineering challenges), the ideas generated by them may not be at a sufficient level of quality and specificity to be useful in high-stakes, high-security, or low-tolerance settings. A promising area of research is idea enrichment, whereby a relevant, useful kernel is identified in an idea and is developed to a level necessary for consideration and adoption by the decision-makers. Second, for platforms that attract significant volume of contributions, it may be difficult to find ideas of high potential. Here the application of machine learning is promising (e.g., Yin et al. [92]). The integration of idea generation platforms with other crowdsourcing models, such as micro-tasking (where workers on MTurk, for example, could be asked to rank and evaluate the submitted ideas) also presents an opportunity for future research.

4) Observational model

Research in this category is aligned with the characteristics of observational crowdsourcing, namely, "a) long-term, and continuous data collection; b) Ill-defined, open-ended tasks; c) at least in part performed out in the world; and d) mostly voluntary in nature" ([27] p.4). Observational crowdsourcing has been successfully used for collecting a large amount of data in different domains such as medical, transportation, online shopping, disaster management, and science. Mobile crowdsourcing, experience sampling, diary studies, self-tracking, and citizen science projects are a few areas that rely heavily on data collected from the crowd [93]. Citizen science involves members of the general public participating in various aspects of scientific research, such as data collection and analysis [94,95]. While citizen science does not always involve crowdsourcing, as it may take a form of community activism or citizen-driven inquiry [28,95,96], these projects frequently involve crowds in data collection (e.g., iNaturalist.org – observations of nature), data analysis (e.g., Zooniverse.org – classification of galaxies from images) and, more rarely, hypothesis generation (e.g., EteRNA vaccine development; see Robson & Green [97]). The data collection types of citizen science fit the observational model of crowdsourcing.

Several domains that fall into this category have a social theme and are driven by pro-social motives of individuals. For example, disaster management and emergency response are areas that rely heavily on the crowd's input. Specifically, the emergence of geo-mobile technologies and crowdsourcing methods changes the landscape of disaster management by allowing citizens to provide rich and real-time data about local adverse events [98]. In their crowdsourcing in disaster management framework, Poblet et al. [98] identified four main roles of the crowd: the crowd as a sensor, the crowd as a social computer, the crowd as a reporter, and the crowd as a micro-tasker. Mobile crowdsourcing for beach monitoring is another example of a crowdsourcing project with a social theme [99]. Crowd-based labels for social-bot detection is another recent example that falls into this category [100].

Crowdsourced data quality is another dominant research stream in this category. Van Berkel et al. [93] mentioned that "carefully considering how and when data can be collected from human participants is key in ensuring a reliable level of human accuracy" (p. 3). Lukyanenko et al. [5] conducted experiments in the citizen science domain and showed that instance-based data collection (i.e., "describe observed instances in terms of any classes or attributes of interest at any level of precision" [p. 626]) compared to the dominant class-based approach (i.e., classify observed object in terms of predefined categories) results in higher accuracy and data completeness, as well as a higher number of discoveries. Specifically, the class-based model results in low accuracy when the crowd is unfamiliar with the defined classes [101]. Therefore, instance-based data collection may be more suitable for open data collection from an undefined crowd.

We found a diverse range of papers with slightly different themes in this category. Unlike in other crowdsourcing models, participants' motivations or the platform structures are sparsely represented in our sample (although papers beyond our sample, such as those published in biology and computer science areas, have explored motivation in observational projects – e.g., [102,103]). Further exploration is required to identify unique sub-themes within this category.

Observational platforms also have notable shortcomings, further highlighting the need for motivating more research on understanding these limitations and considering strategies for mitigating them. First, a notable limitation of observational platforms is the reliance on a stable cohort of users who often, for altruistic or intrinsic motives, choose to participate in these platforms. However, with the growing success of crowdsourcing, there has been an explosion of observational crowdsourcing projects. For example, in the domain of citizen science alone, there are over 1300 projects registered on SciStarter.com (the leading catalog of projects). This results in competition among the projects for members, and a corresponding research opportunity is how to share the user base among projects [104]. Second, ensuring reliable, trustworthy, and high-quality data can be significantly more challenging on observational crowdsourcing compared to other models. This is largely because observational projects are wide open to the general public, often seek larger participation, and frequently involve anonymous users (compared to, for example, micro tasks that engage already registered users with a reputation based on prior crowdsourcing tasks). The data quality approaches in observational crowdsourcing discussed above can be further augmented by integrating observational crowdsourcing with other models, such as micro tasks, where quality controls can be stricter. Third, a notable challenge on observational platforms arises because of its open nature. The observational platforms almost universally display the data points contributed by all members (in contrast to other crowdsourcing models, where data points are frequently kept private and not shared with the participants). There are several implications of this common characteristic of these platforms. For example, the long tail participation dynamics, whereby few active users contribute the majority of the observations, is known to affect the resulting data [105]. Another possibility is the emergence of grassroots hierarchy, dominated by few active participants. An important research direction is leveraging the characteristics of other crowdsourcing models - such as those in which the nature of participation is different - in attempting to mitigate some of the shortcomings of observational crowdsourcing.

5.2. Intra-system perspective: nature of system components and stakeholders

This section briefly summarizes the key topics from an intra-systems perspective. Since several studies have been discussed in detail in the previous section, we mainly compare the literature from system components' perspectives in different environments.

1) Crowd (Solver)

Several crowd-related themes have emerged in our topic analysis, including crowd solvers' motivations, intentions, engagement, strategies, and other behaviors such as knowledge sharing. Solver strategies are mainly applicable and investigated in the crowdsourcing contest model. Solvers need to strategically participate in competitions to win the reward without incurring a huge cost [56]. These strategies include deciding when to enter a contest, when to submit a solution, how much effort to allocate, and whether to compete as teams or as individuals.

Unlike solver strategies, solvers' motivations have been an important research theme across most crowdsourcing system models. These motivations are primarily categorized as extrinsic and intrinsic motivations and include motivating factors such as monetary rewards, skill enhancements, autonomy, enjoyment, and trust [106]. However, these motivations can differ based on the crowdsourcing model. It could vary from winning monetary rewards in the contest model to pro-social motives in some citizen science projects.

2) Platform

Crowdsourcing platforms vary in scope, types of tasks that they handle, motivations, and subject domain. Some seekers have their own platforms (e.g., Dell Ideastorm, Zooniverse for Galaxy Zoo), while others use intermediary platforms to interact with solvers (e.g., Kaggle, Innocentive). Different contest platforms focus on different domains, such as TopCoders for software development, CrowdMed for medical crowdsourcing, and Kaggle for data science projects, to name but a few.

As explained earlier, platforms consist of platform technology and platform structures. Research on crowdsourcing contest platforms mainly focused on platform reward structures and platform technology (e.g., design characteristics), including feedback criteria and the task evaluation process. The contest model usually has a monetary reward (or, occasionally, multiple rewards), and one or very few best-performing solvers are entitled to the reward. Based on all-pay auction and tournament theories, several studies have explored how to optimize the reward structure in the contest model. Researchers have also investigated how gaming elements (e.g., performance medals, public leaderboards) can be used to motivate solvers and intensify the competition among participants.

Much of the IS and related business research in this area falls at the center of the social-technical continuum, explicitly focusing on the interaction of crowd and platform technology. For example, interim performance feedback through a leaderboard (platform technology) encourages solver motivation/ effort.

The solution evaluation process is another important platform-related topic. Different platforms use different methods, such as a crowd-based evaluation process (e.g., crowd voting), expert-based evaluations, machine learning/ analytics methods, or multiple methods [107]. Some scholars have also explored the effectiveness of different evaluation processes.

In addition to crowd motivations, the platform providers must also be cognizant of crowd characteristics such as crowd diversity, experience, and crowd size. Crowds with diverse knowledge and domain expertise may help solve complex problems in crowdsourcing contests. On the other hand, crowd size and quantity of solutions, rather than knowledge diversity and expertise, are critical for mass data collection tasks. Some idea generation platforms look for a specific crowd, such as consumers of a particular product. Attracting the right crowd is critical to enhancing overall system outcomes.

3) Tasks/Seekers

In comparing the nature of tasks across the four crowdsourcing models, each exhibits distinct characteristics tailored to its specific purpose. The Contest Model, exemplified by platforms like Kaggle and TopCoder, involves addressing complex and innovative problems within well-defined domains, such as data science or software development, often requiring only one or a few high-quality solutions. Seekers play a more active role on these platforms compared to others, drawing more solvers through attractive incentive schemes and task presentations. Conversely, the Idea Generation Model, exemplified by Dell IdeaStorm, fosters collaborative idea generation with an emphasis on producing multiple innovative ideas for new product or feature developments, particularly from identified groups such as consumers. The Micro-tasking Model, represented by MTurk and MobileWorks, offers simple and repetitive tasks, typically of short duration and completed independently. This model covers tasks such as surveys, classification, labeling, and data entry, which often require a high quantity of output. Last, the Observational Model, as seen in iSpot and GasBuddy, presents simple, open-ended tasks relying on continuous data collection from a distributed crowd. This is particularly suitable for reporting observations or measurements that involve very high quantity, often requiring mass or continuous data collection efforts.

Compared to other sourcing mechanisms, such as outsourcing and offshoring decisions, there is a paucity of literature related to organizational perspectives on crowdsourcing [9]. Even after an organization has decided to crowdsource, the process involves a sequence of solver- and platform-related decisions, such as involving internal employees, consumers, or open crowds and whether to use an in-house platform or a third-party intermediatory platform. This topic could, therefore, be another important area for future studies.

Few studies have explored crowdsourcing from an organizational perspective. For example, based on survey data gathered from 161 organizations, Ye and Kankanhalli [106] identified perceived benefits of cost reduction, brand visibility, and access to specialized skills as some factors that positively influence organizations' intentions to crowdsource. In contrast, codification and solution evaluation costs negatively influenced the intentions to crowdsource. Afuah and Tucci [108] developed a model to explain the factors influencing the probability of crowdsourcing, including problem characteristics, the knowledge required, the crowd, the evaluators and the solution to be evaluated, and information technology.

Likewise, despite the growing trend of crowdsourcing being not only an activity implemented by organizations, but also by individuals, there is a paucity of research on crowdsourcing from the perspective of individual seekers. For example, with the help of platforms, such as MTurk, ordinary citizens can post tasks related to their own needs. This is consistent with the notion of empowered users – non-IT professionals who are increasingly autonomous and active in the use of information technology [109]. However, we understand very little about the extent of this practice, what motivates individuals to sponsor crowdsourcing activities, how their approaches may differ from those of organizations, and which designs of crowdsourcing are better suited for individual versus organizational crowdsourcing. This creates a vast opportunity for future scholarship on what we label as *privately sponsored crowdsourcing* – defined as crowdsourcing tasks which are designed and sponsored by private citizens to satisfy their private needs.

5.3. Crowdsourcing themes by inter- and intra-system perspective

Based on the conceptual model (Fig. 1), Table 5 presents topic themes from inter-system (horizontal axis) and intra-system (vertical axis) perspectives. Following the problematization approach [14], the current table will open up new conversations for future studies. Specifically, the table presents an overview of key themes of crowdsourcing models, the nature of the stakeholders involved in each model, the key research topics with sample literature for each model, and the research gaps. In other words, this is a two-dimensional matrix where one dimension represents distinct crowdsourcing models, and the other represents social and technical systems system components.

From a system's perspective, we found more research related to platform technology/mechanism and less research related to platform management. Specifically, the crowdsourcing contest model is rich in platform design characteristics (i.e., platform technologies) such as feedback mechanisms, gaming elements, solution quality dimensions, filtering mechanisms, and reward structures but lacks research related to the platform policies, regulation, and ethics (i.e., platforms management). Micro-tasking is the only model focusing heavily on platform management, such as the effectiveness of platform governance and ethics/fairness. However, there is a lack of research on feedback mechanisms and solution quality dimensions in the micro-tasking domain. When it comes to solver strategies, research is mainly limited to the crowdsourcing contest model, even though it is also applicable to other platforms up to a certain extent. In addition, we observed that much of the crowdsourcing research focuses on individual components of the systems without considering a holistic view of the system.

6. Discussion and implications

Based on the inter-system and intra-system perspectives, we identified several key themes in the crowdsourcing literature, as presented in Table 5. As discussed earlier, the crowdsourcing system is composed of interrelated elements but extant studies have largely neglected to examine their interrelationships. Thus, crowdsourcing research needs to take a holistic systems perspective and focus on the relationships among the social and technical aspects of the system rather than on optimizing individual components. Advocates of General System Theory have long argued that complex systems – such as biological systems – cannot be understood (and managed) by studying their parts in isolation [21]. A holistic view that considers their interactions is necessary to optimize the performance of such systems (e.g., [128]). Furthermore, emphasizing the whole system and trying to maximize its overall performance can lead to deeper insights about its constituent parts [21].

The systems perspective of crowdsourcing is shown in Fig. 8. It depicts the intra-system perspective of a crowdsourcing system. As evident from this figure, platform structures, platform technology, people, and tasks are coupled together in a complex whole. As our earlier results show, many insights can be gleaned from considering how these parts interact. For example, crowd effort can be increased by inducing competition through attractive prize structures and open leaderboards. This shows that crowd characteristics (motivations), platform structures (prize), and platform features (leaderboard) interact with each other and influence crowd effort.

In addition to the insights on the importance of taking the systems perspective, our findings advance the understanding of individual crowdsourcing models, or archetypes of these crowdsourcing systems. Based on our analysis, we identified four distinct crowdsourcing models, namely, the contest model, idea generation model, micro-tasking model, and observational model. We found that the nature of the tasks is different in each model. Research in the area of the contest model seems to focus more on the platform features (e.g., feedback mechanisms, discussion boards, evaluation mechanisms) and crowd characteristics/

Table 5
Key themes by crowdsourcing system models and system components.

		Inter-System Perspective			
		Contest *Model* (e.g., Kaggle, TopCoder)	Idea Generation Model (e.g., Dell IdeaStorm)	Micro-tasking Model (e.g., MTurk, Mobileworks)	Observational Model (e.g., iSpot, GasBuddy, Waze)
Intra-System Perspective	**Task**	*Nature of the task:* • Complex and innovative problems • Involves solving a specific problem with a defined domain. • Involves tasks such as predictive modeling, algorithm optimization, solving medical mysteries.	*Nature of the task:* • Innovative problems • Often encourage collaborative refinement • Involves tasks such consumers generate ideas for new product development	*Nature of the task:* • Simple and repetitive [68] • Well-defined [27] • Tasks are often short in duration and need to be completed independently by distributed workers. • Involves tasks such as surveys, classification, labeling, and data entry.	*Nature of the task:* • Simple tasks • Open-ended • Tasks generally relied on continuous data collection from geographically distributed crowds. • Involves tasks such as reporting observations or measurements (e.g. wildlife sightings or traffic patterns)
		Solution Quantity: Requires one or very few good high-quality/ groundbreaking solutions	*Solution Quantity:* Several innovative ideas	*Solution Quantity:* High quantity	*Solution Quantity:* Very high quantity (mass/ continuous data collection)
		Other Task Characteristics: • Task complexity (analyzability, variability), variety, autonomy, tacitness [110]; task modularity(e.g., TopCoders) • Perceived quality of task presentation and emotional tone [107] attract solvers	*Other Task Characteristics:* • Provide exemplars [91]	*Other Task Characteristics:* • Job autonomy, task variety, task significance, task intrusion, and task compensation influence workers' continuous participation [111]	*Other Task Characteristics:* • often require field observations • often need equipment (e.g. camera, binoculars)
	Platform Structures	*Reward/compensation*: • Usually, monetary rewards to winners [58] • Optimum reward structure	*Reward/compensation:* • Range from cash prices to non-monetary prices, such as iPods and vouchers [88]	*Reward/compensation:* • Micro-payments (X. [67]) [112]	*Reward/compensation:* • Mostly voluntary [27]
		Platform Policies and Ethics • Norms-based intellectual property [113] • Lack of research in this area	*Platform Policies and Ethics* • Lack of research in this area	*Platform policies and Ethics* • Effectiveness of platform governance [6] Ethics and fairness [72,114]	*Platform Policies and Ethics* • Lack of research in this area
	Platform Technologies	*Feedback:* • Blind Vs Unblind [61] • Interim/ in-process feedback [2,56] • Effect of aspects of rating feedback on submission behaviors [115]	*Feedback:* • Peer voting and in-process feed-back [90]	*Feedback:* • Digital feedback valence influences creative performance [116] • Lack of research in this area	*Feedback:* • Lack of research in this area
		Solution Quality dimensions and antecedents: • Prediction accuracy, relative performance • Solver/ team characteristics such as skill, diversity, effort, self-efficacy, motivation, and team size [56,59] • Contest characteristics such as reward structure, duration, complexity, feedback structure *Filtering/ Evaluation Methods:* • Experts-based • Crowd-based • Analytics/ ML-based (e.g., Kaggle)	*Solution Quality dimensions and antecedents:* • Novelty, feasibility, relevance, customer benefit, and specificity [84,117] • Readability & perceived ease of use [86] • Community participation [85] • User experience, idea presentation, feedback valence (Q. [83]) *Filtering/ Evaluation Methods:* • Crowd-based: peer(crowd) voting / ranking [118]	*Solution Quality dimensions and antecedents:* • Heuristic-based dynamic label allocation strategies to enhance quality (J. [78]) • Lack of research in this area *Filtering/ Evaluation Methods:* • Experts-based • Machine learning approaches for filtering survey responses [75]	*Solution Quality dimensions and antecedents:* • Data accuracy and completeness [5,93] *Filtering/ Evaluation Methods:* • Cross- and peer-validation [93] • Statistical techniques that exploit data redundancy • Expert field verification

(*continued on next page*)

Table 5 (*continued*)

	Inter-System Perspective			
	Contest *Model* (e.g., Kaggle, TopCoder)	Idea Generation Model (e.g., Dell IdeaStorm)	Micro-tasking Model (e.g., MTurk, Mobileworks)	Observational Model (e.g., iSpot, GasBuddy, Waze)
		• Experts-based • Rating scale vs. preference market [86]		
	Other design elements:Competitive/ collaborative elements: • Gaming elements (e.g., Leaderboards) [56] • Collaborative elements (e.g., discussion forums, kernels) [57,63]	*Other design elements:* • Generative co-creation (discussions during crowdsourcing for innovation) [119]	*Other design elements* • Digital work control (micro-task programmability, payment automation, standardization, and risk mitigation) (X. (Nancy) [111])	*Other design elements* • Instance-based approaches to collecting data [120] • Basic classes during conceptual modeling in UGC & other related environments; Guidelines for conceptual modeling in UGC [121,105]
Crowd	*Form of participation:* Individuals or teams [122]	*Form of participation:* Mainly individuals	*Form of participation:* Mainly individuals	*Form of participation:* Mainly individual
	Crowd characteristics: • Crowd size – varies • Crowd diversity - Knowledge/ skill diversity is beneficial [123]	*Crowd characteristics:* • Crowd size – varies • Crowd diversity- Generally targeted groups such as consumers of a product	*Crowd characteristics:* • Crowd size – generally fixed • Crowd diversity – Skill/ knowledge diversity is usually not much of a concern • The agency of workers, their culture, and their own context [124]	*Crowd characteristics:* • Crowd size – varies, generally very large • Crowd diversity – dimensions vary based on data (e.g., location diversity for apps like GasBuddy and Waze)
	Motivation/ demotivation factors: • Learning • Peer recognition • Monetary rewards • Superstar effect [64]	*Motivation/ demotivation factors:* • Learning, direct compensation, self-marketing, and social motives [88]	*Motivation/ demotivation factors:* • Meaningfulness of work [71] • Unfair wages • Relatedness, existence, and growth needs [70] • Community participation • Job satisfaction and antecedents of turnover intentions [73,125] • Worker empowerment and exploitation (X. (Nancy) [69]) • Job characteristics • Compensation, enjoyment, and microtime structure [126]	*Motivation/ demotivation factors:* • Pro-social/ altruistic motives dominate [99] • Temporal motivations of volunteers [127]
	Crowd Strategies: • Entering strategies • Teaming strategies • Submission strategies [56] • Effort allocation strategies [56]	*Crowd Strategies:* • Lack of research in this area	*Crowd Strategies:* • Lack of research in this area	*Crowd Strategies:* • Lack of research in this area

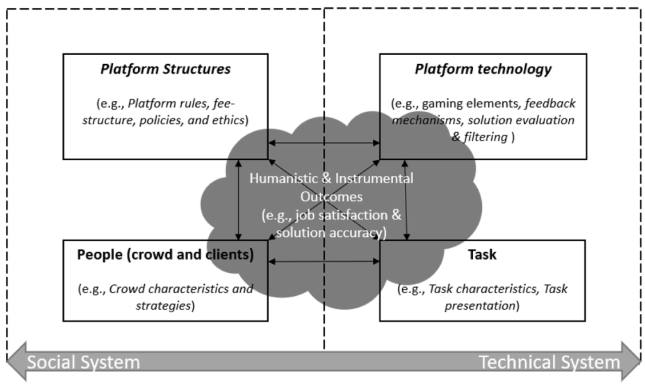

Fig. 8. Intra-system perspective of crowdsourcing system.

behaviors (e.g., crowd size, crowd strategies) and their interactions. Not much research has been done related to platform structures (e.g., policies, ethics) except fee structures. Also, many platform features are studied individually but can be presented simultaneously on platforms. The contest research lies closer to the center of the social-technical continuum in the IS discipline (see [35]). However, instrumental objectives (e.g., the prediction accuracy of a solution model) received more attention than the humanistic objective (e.g., solver satisfaction) in the contest model.

Research on idea generation models primarily focuses on topics with instrumental objectives such as idea quality and evaluation mechanisms. A few studies focused on humanistic objectives such as participants' motivations. It is fair to say that many studies have focused on the interaction between the crowd and the platform features with scant regard for topics related to platform policies, ethics, and trust.

Unlike other models, research on micro-tasking has focused more on humanistic objectives such as worker satisfaction. Research in this area is skewed slightly toward social aspects of the social-technical continuum. Solution quality is an important research direction for future research in this model. On the other hand, data quality research plays a vital role in the observational model. Even though the observational model is widely used for tasks with social themes, humanistic objectives have not received much attention in this model. Based on the identified gaps, we propose sample research directions in the following section.

Not surprisingly, much of the research on crowdsourcing adheres to a scientific or analytical paradigm that proceeds with a set goal in mind and endeavors to isolate problems and explain them based on a deductive and reductionistic method of inquiry [21]. Unlike the systems approach or the systems paradigm [22], such an approach focuses on a narrow aspect of the "crowdsourcing system" and often fails to deepen our understanding of the whole crowdsourcing phenomenon and its underlying assumptions. An integrated, synthetic view based on inducing from isolated parts (i.e., the various stakeholders and the platform) may give us a greater appreciation of what it takes to expand the boundaries of crowdsourcing and enrich our understanding of the

Table 6
Sample research directions.

Contests model
Platform technology and interactions
RD1: Explore a more holistic approach to investigate the overall effect of platform design features on the outcome of a crowdsourcing system. The one-size-fits-all model is ineffective; therefore, we must examine which combination of features works best for any given task characteristics rather than investigate the effect of individual features.
RD2: Explore platform features - specifically recommendation systems - to facilitate contest selection decisions for solvers based on crowd and task characteristics and to find desirable team members to enhance the solution quality.
RD3: Explore the effect of platform features on humanistic system outcomes?
Platform structures and interactions
RD4: Explore crowdsourcing contest platform structures such as policies, ethics, and their effectiveness based on the task and crowd characteristics.
Micro-tasking model
Platform technology and interactions
RD5: Explore better platform mechanisms such as introducing gaming elements and community elements to enhance worker engagement and motivation and make micro-tasking work more meaningful.
RD6: Explore better platform mechanisms to identify potential low-quality input based on techniques such as user behavior analytics.
RD7: Explore effective feedback mechanisms in micro-tasking to enhance both instrumental (e.g., solution quality) and humanistic outcomes (e.g., crowd motivations).
RD8: Examine the impact of generative AI on micro-tasking model in terms of its potential to either enhance human effort or replace certain micro-tasks entirely.
Platform structures and interactions
RD9: Explore what can be done from the platform governance perspective (e.g., policies) to protect crowd workers in micro-tasking platforms.
Idea generation model
Platform technology and interactions
RD10: Experts and crowd evaluate ideas using different perspectives (e.g., novelty, implementability, cost, and presentations). Explore how to optimize the idea evaluation process by combining different techniques (e.g., crowds, expert, machine learning) and through platform design changes.
RD11: Explore how to enhance humanistic system outcomes through platform changes (e.g., gaming elements).
RD12: Explore the effect of AI-powered ideation on traditional crowd-based idea generation model and potentially lead to "collective intelligence" that can engender more novel solutions.
Platform structure and interactions
RD13: Explore idea generation model's policies and their effectiveness based on the task and crowd characteristics.
Observational model
Platform technology and interactions
RQ14: Explore non-monetary reward/compensation structures to attract and motivate the crowd without monetary incentives.
RQ15: Explore how to incorporate feedback and other platform mechanisms to improve data quality in mass data collections.
Platform structure and interactions
RQ16: Explore platform governance mechanisms of mass data collection and collaborative communities and their effectiveness considering the task and crowd characteristics.
RQ17: Explore how Big Data technologies and Artificial Intelligence, particularly Large Language Models, can be utilized to enhance the efficiency and precision of identifying patterns and insights within large and noisy crowdsourced datasets.
Cross- model learning and idea fertilization
RQ18: Explore ideas, concepts, methods and approaches shown to be useful in one crowdsourcing context in another context.
General addition across all models
RQ19: Explore the balance between the level of training and diverse capabilities of crowd workers to achieve the best outcomes across various tasks, considering that excessive training might hinder creativity.
RQ20: Explore the overarching impact of generative AI across all crowdsourcing models, focusing on how AI tools and capabilities can enhance or disrupt traditional crowdsourcing dynamics.
RQ21: Explore how does the adoption of crowdsourcing strategies impact the innovation and competitive advantage of firms across different industries?

interplay among its various components [21].

6.1. Future research directions

The research directions articulated in Table 6 were based on the conceptual model presented in Fig. 1, the gaps identified by our preceding analyzes of the literature (see Table 5), and expert consultation. Senior scholars with expertise in crowdsourcing augmented our analysis by drawing our attention to the effects of LLMs (large language models) and AI services on crowd-based models (e.g., see [129]). Sample research directions proposed in Table 6 focus on the technical and social design of different types of crowdsourcing models (Contests model, Micro-tasking model, Idea generation model, and Observational model) and the interaction between social-technical elements in the systems.

Additionally, our analysis reveals that gaps and areas of saturation for the different models of crowdsourcing do not coincide. For example, strategies for selecting tasks have been studied for the contest models but are virtually absent for observational crowdsourcing. Similarly, nonmonetary rewards have been investigated in observational crowdsourcing, but have scarcely been examined in contests, idea generation, and micro-tasking models. These insights point to an important opportunity that has escaped the research community so far: cross-pollination of concepts, theories, solutions, and methods across the different crowdsourcing communities. Consider one such research question: how do we leverage altruistic motives that have proven to be effective in citizen science in crowdsourcing contests? We capture this opportunity and other topics that are novel to all the models at the end of Table 6.

6.2. Implications

Our study has several implications for both academic researchers and practitioners. First, our study introduced a two-dimensional (i.e., inter-system and intra-system) conceptual framework to guide research in the crowdsourcing domain. This framework provides a holistic picture of crowdsourcing systems and can easily be extended as new models and components emerge.

Based on this framework, we performed a detailed review of the extant IS and organizational literature to address research questions concerning different crowdsourcing models, the nature of tasks they solve, and the role of stakeholders in these distinct models using a non-traditional text-based methodology. Table 5 summarizes the four main themes of crowdsourcing system models identified (contest model, micro-tasking model, idea generation model, and observational model) and the nature of stakeholders and systems components for each crowdsourcing model. Based on our analysis, we identified current gaps in the literature and offered directions for future research on crowdsourcing (see Table 6).

From the intra-system perspective, our study articulated a socio-technical framework to understand and conceptualize the interactions between technical and social features of crowdsourcing systems. The socio-technical view of crowdsourcing systems presented in our study advocates a holistic approach that emphasizes the interdependence and interactions among platform structures (e.g., policies, rules, ethics), people (crowd's characteristics, motivation, and strategies), platform technology (crowdsourcing platforms' interface features), and tasks (crowdsourcing tasks' complexity, modularity, and volume). A socio-technical perspective will ensure that we do not subordinate social imperatives such as learning, adaptation, and morality to instrumental interests aimed at making our systems technically more efficient [21].

From the inter-system perspective, we identified distinct crowdsourcing models, their components, and current research related to these distinct models. This not only helps to identify current research gaps within different crowdsourcing models but also allows us to identify transferable knowledge and best practices across distinct models. For example, gaming elements have mainly been used in the crowdsourcing contest model; however, these can also be used to motivate crowd participants in the other crowdsourcing models.

Our analysis reveals that social and technical aspects of crowdsourcing have not been examined holistically. Consequently, there is an opportunity to deepen our understanding of crowdsourcing systems by investigating the dynamics of interactions among the socio-technical dimensions of such systems. Crowdsourcing research needs to take a more holistic, systemic view and explore the interdependencies of parts comprising the socio-technical system rather than focusing on its individual components. This perspective highlights the opportunities for advancing theoretical development in the crowdsourcing literature. Specifically, the sample research questions provided (Table 6) show the gaps in the literature regarding the social and technical aspects of the crowdsourcing platform features and how they could possibly be influenced by the crowd and task characteristics. The questions raised offer opportunities for information systems academic researchers to advance our understanding of crowdsourcing systems. A systems approach rather than a reductionistic one will also compel researchers to reflect on the underlying assumptions and objectives of crowdsourcing, possibly leading to innovative ways of using crowdsourcing across a variety of domains [21,22].

The study has implications for crowdsourcing system stakeholders. First, from the practitioners' perspective, categorizing crowdsourcing system models helps identify a suitable model based on the task at hand. The contest system model is ideal for complex tasks searching for breakthrough or innovative solutions. These tasks demand solvers with a diverse set of skills. Skill and experience diversity help solvers look at the problem from multiple perspectives and evolve creative solutions. Many contest models allow solvers to participate as individuals or as teams. On the other hand, micro-tasking platforms are suitable for simple and repetitive tasks that do not require much skill or creativity. Idea generation systems are for a more targeted set of crowds, such as consumers of a product. Crowd participants with domain-related experience and/ or expertise help in such tasks, whereas the size of the crowd matters for mass data collection activities. Unlike the contest or micro-tasking models, direct financial incentives may not be associated with the observational crowdsourcing model.

Second, a holistic socio-technical view of a crowdsourcing system would also inform practitioners' strategies for developing and managing successful crowdsourcing systems models. Organizations trying to incorporate different crowdsourcing systems models should consider the systems perspective of crowdsourcing. A crowdsourcing platform's social and technical aspects are interconnected with the characteristics of the task at hand and the characteristics of the solvers. For example, task characteristics (complexity, modularity, and volume) and crowd characteristics can impact the crowdsourcing platform when designing a compensation structure, feedback, and solution evaluation mechanisms. On the other hand, changes in the policies or the technical design of a crowdsourcing platform would potentially impact the crowd's motivation and subsequent participation and, consequently, the quality of the solutions. Given this backdrop, organizations adopting crowdsourcing models, platform developers, and policymakers should focus on the dependencies – both social and technical – that will enhance the efficacy of the whole model rather than on optimizing individual components. In the current study, the focus is on an individual crowdsourcing platform. Future research can be conducted to study how crowdsourcing (as a "system") co-exists with or complements other systems in an organization.

7. Conclusion

In this study, we conducted a rigorous and comprehensive review of the academic literature on crowdsourcing, identifying key trends, gaps and opportunities. Prior reviews of crowdsourcing, with a few notable exceptions (e.g., [9,10]), have focused on either a specific type of crowdsourcing platform or a particular aspect of crowdsourcing. Our study makes an important contribution by advocating a holistic approach to understanding the crowdsourcing phenomenon. The basis for our recommendations rests on the theoretical foundations of the systems approach [20,21,22] and socio-technical systems [34].

Our findings show that crowdsourcing contest-related and idea-related studies dominate the crowdsourcing literature in IS and business journals. Furthermore, many studies have adopted a rather narrow view of crowdsourcing by focusing exclusively on individual features in isolation. We contend that such a siloed approach fails to consider the interrelationships among the individual components that comprise a crowdsourcing system. Consequently, a holistic and comprehensive view of crowdsourcing has eluded scholarship, thereby precluding practice from fully understanding how the features can collectively improve the performance of such systems. Considering this, we conducted a literature review and analyzed our findings using inter-systems and intra-systems perspectives. Based on our analysis, we provide a research agenda for four distinct system models: contest model, micro-tasking model, idea model, and observational model. Furthermore, we have explored different aspects of each system model from system components' perspectives, such as crowd solvers, platform providers, and clients.

From the practitioner's perspective, the study helps platform providers to identify the interrelated elements in crowdsourcing systems, which is crucial to instituting platform changes that will make the crowdsourcing system more efficacious. The study also emphasizes the importance of taking a systemic or holistic view when incorporating such design changes. Changing one feature could indirectly impact other variables and result in unexpected consequences. From a theoretical or academic perspective, the study has provided a comprehensive review of the crowdsourcing literature in the IS domain and articulated a roadmap to further the boundaries of knowledge in this area. Thus, this study's findings and future research directions provide valuable guidelines to IS researchers and crowdsourcing practitioners (i.e., clients, solvers, and platform providers) as they endeavor to unlock more value from crowdsourcing.

Submission declaration and verification

We confirm that this work (or closely related research) is original and has not been published elsewhere, nor is it currently under consideration for publication elsewhere.

Disclosure instructions

During the preparation of this work the author(s) used Grammarly and Chatgpt to check the writing errors (grammar and spelling) and improve readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Indika Dissanayake: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Sridhar P. Nerur:** Writing – review & editing, Writing – original draft, Formal analysis. **Roman Lukyanenko:** Writing – review & editing, Writing – original draft. **Minoo Modaresnezhad:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

None.

Appendix A

Figs. A1, A2, and A3 represent the demographic overview of the papers, showing the number of publications, the top countries based on publication counts, and the number of publications by outlet, respectively.

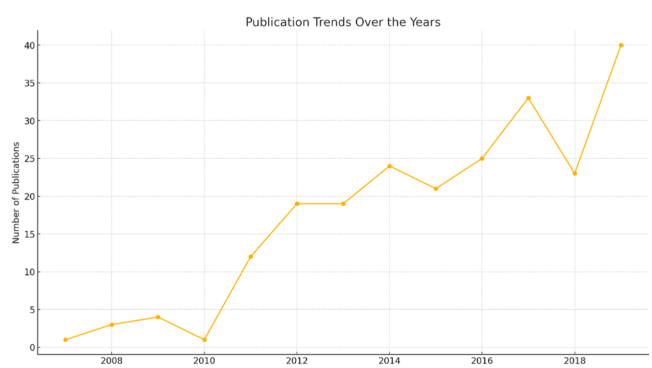

Fig. A1. Publication trend over the years.

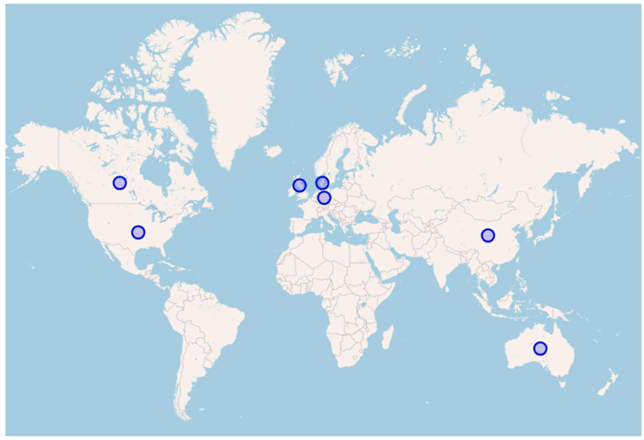

Fig. A2. Top countries by the number of publications.

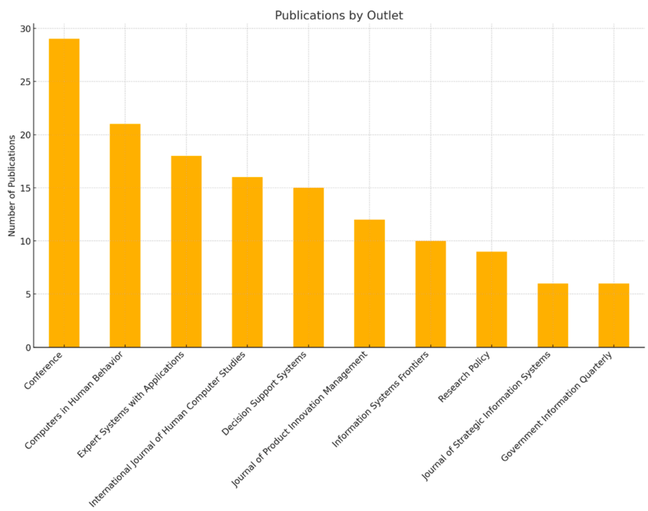

Fig. A3. Number of publications by outlet.

Table A1
NMF topic analysis.

Topic ID	Key Words	Main theme
Inter-system perspective (Crowdsourcing system models)		
N1	idea, generate, implement, generation, organization, ideation, implementation, evaluation, convergence, innovation, cognitive, numb, ideators, submit, successful, contributor, creator, support, potential, development	**Idea generation**
N2	contest, contestant, submission, innovation, reward, platform, solution, prize, performance, win, participant, crowdsourcing, award, winner, size, behavior, duration, optimal, superstar, separate	**Crowdsourcing contests** • Solvers' effort (e.g., # submission)
N5	solver, contest, seeker, win, effort, experience, open, task, loss, innovation, mediate, participation, participate, incentive, orient, ideation, affect, engagement, ort, reverse team, performance, tournament, competition, effort, capital, competitive, platform, forecast, dominance, prediction, crowdsourcing, efficacy, intellectual, social, member, compete, forecaster, participant, affect	• Reward(s) or Prize(s)
N15	datum, quality, collection, human, participant, accuracy, sample, people, approach, science, collect, review, crowdsourced, label, analysis, time, contribution, contributor, train, instance	**Crowdsourcing for data collection** • Crowd-based forecast and crowd sensing (e.g., mobile sensing to collect real-time traffic data) • Surveys
N6	work, crowdworkers, worker, crowdwork, platform, career, job, digital, employment, mturk, autonomy, pay, perspective, form, experience, context, understand, governance, creative, meaningfulness	**Micro-tasking** • Crowdwork • Crowd-based labeling and classification
N3	worker, algorithm, label, task, reliability, assignment, spatial, crowdsourcing, classification, method, propose, multi, approach, estimation, group, expertise, recommendation, judgment, cost, quality	
N11	government, open, citizen, public, project, science, policy, sector, innovation, agency, medium, network, social, challenge, crowd, society, management, governance, administration, coproduction	**Other crowd-based collaborative network communities** • Wikipedia; social-learning networks; social media for disaster management;

(*continued on next page*)

Table A1 (*continued*)

Topic ID	Key Words	Main theme
N4	user, content, model, social, mobile, contribution, hierarchy, frame, platform, generate, topic, propose, expert, ugc, recommendation, incentive, approach, distance, base, item	• Co-creation; user-generated content • Citizen science & disaster management
Intra-System Perspective (Crowdsourcing Stakeholders Perspectives)		
N10	feedback, positive, quality, performance, negative, customer, frame, creative, subsequent, intensity, submission, entry, ideation, component, motivate, direct, tournament, online, experiment, firm	**Platform perspective***Platform technology:* • Feedback
N14	problem, solve, solution, search, decision, crowd, circumstance, supplier, design, agent, seeker, innovation, visualization, facility, structure, uncertainty, crowdsource, tool, algorithm, optimal	• Solution evaluation mechanism • Role as IT service provider*Platform structures:*
N16	task, crowdsourcing, perceive, contributor, allocation, quality, decision, spatial, crowd, mechanism, framework, performance, server, budget, result, base, type, numb, work, intention	• Model; platform governance and controls
N12	service, client, capability, vendor, provider, trust, crowdsourcing, model, cloud, organization, software, intermediary, technology, cost, outsource, compute, business, stem, develop, deliver	• Provider trust
N9	knowledge, share, social, network, learn, paradox, customer, structure, trajectory, periphery, interaction, theory, core, online, innovative, process, economy, human, ck, support	**Crowd/ Solver perspective** • Knowledge sharing in crowdsourcing (e.g., willingness to share knowledge; knowledge sharing patterns)
N13	community, online, employee, engagement, innovation, content, software, reminder, norm, ouics, advice, creativity, source, individual, access, firm, eol, opensourcing, contribute, support	• User motivation and engagement (e.g., gamification; extrinsic and intrinsic motivations)
N7	motivation, intrinsic, participation, extrinsic, game, crowdsourcing, engagement, gamification, volunteer, contribution, participant, player, sustain, reward, effort, mediate, design, motivate, motivational, efficacy	
N17	product, consumer, market, brand, customer, designer, generate, sale, firm, luxury, purchase, concept, equity, design, source, review, company, rating, hotel, average]	**Organization/ Client/ Seeker perspective** • Internal crowdsourcing; organizational role
N0	crowdsourcing, internal, organizational, innovation, organization, process, employee, firm, collaboration, design, enable, practice, crowd, phenomenon, insight, year, form, framework, external, work	• Organizational motivations, challenges; intentions to crowdsource

References

[1] J. Howe, Crowdsourcing: How the Power of the Crowd is Driving the Future of Business, Random House, 2008. https://www.penguinrandomhouse.com/books/83579/crowdsourcing-by-jeff-howe/.
[2] L. Jian, S. Ba, L. Lu, L.C. Jiang, S. Yang, Managing the crowds: the effect of prize guarantees and in-process feedback on participation in crowdsourcing contests, Manag. Inf. Syst. Q. 43 (1) (2019) 97–112.
[3] G. Kazai, J. Kamps, N. Milic-Frayling, An analysis of human factors and label accuracy in crowdsourcing relevance judgments, Inf. Retr. Boston. 16 (2) (2013) 138–178, https://doi.org/10.1007/s10791-012-9205-0.
[4] M. Knaeble, M. Nadj, A. Maedche, N. Loewe, Toward user-adaptive interactive labeling on crowdsourcing platforms, in: *CHI 2022 Workshop - REGROW: Reimagining Global Crowdsourcing for Better Human-AI Collaboration*. Conference on Human Factors in Computing Systems (CHI 2022), New Orleans, LA, USA, 2022, 30.04.2022 –06.05.2022, https://publikationen.bibliothek.kit.edu/1000146670.
[5] R. Lukyanenko, J. Parsons, Y.F. Wiersma, M. Maddah, Expecting the unexpected: effects of data collection design choices on the quality of crowdsourced user-generated content, MIS Q. 43 (2) (2019) 623–647, https://doi.org/10.25300/MISQ/2019/14439.
[6] E. Gol, M.-K. Stein, M. Avital, Crowdwork platform governance toward organizational value creation, J. Strateg. Inf. Syst. 28 (2) (2019) 175–195, https://doi.org/10.1016/j.jsis.2019.01.001.
[7] E. Estellés-Arolas, F. González-Ladrón-De-Guevara, Towards an integrated crowdsourcing definition, J. Inf. Sci. 38 (2) (2012) 189–200.
[8] N.H. Thuan, P. Antunes, D. Johnstone, Factors influencing the decision to crowdsource: a systematic literature review, Inf. Syst. Front. 18 (1) (2016) 47–68, https://doi.org/10.1007/s10796-015-9578-x.
[9] D. Nevo, J. Kotlarsky, Crowdsourcing as a strategic IS sourcing phenomenon: critical review and insights for future research, J. Strateg. Inf. Syst. (2020).
[10] Y. Zhao, Q. Zhu, Evaluation on crowdsourcing research: current status and future direction, Inf. Syst. Front. 16 (3) (2014) 417–434, https://doi.org/10.1007/s10796-012-9350-4.
[11] A. Ghezzi, D. Gabelloni, A. Martini, A. Natalicchio, Crowdsourcing: a review and suggestions for future research, Int. J. Manag. Rev. 20 (2) (2018) 343–363, https://doi.org/10.1111/ijmr.12135.
[12] F.R. Assis Neto, C.A.S Santos, Understanding crowdsourcing projects: a systematic review of tendencies, workflow, and quality management, Inf. Process. Manag. 54 (4) (2018) 490–506, https://doi.org/10.1016/j.ipm.2018.03.006.
[13] M. Modaresnezhad, L. Iyer, P. Palvia, V. Taras, Information technology (IT) enabled crowdsourcing: a conceptual framework, Inf. Process. Manag. 57 (2) (2020) 102135, https://doi.org/10.1016/j.ipm.2019.102135.
[14] M. Alvesson, J. Sandberg, The Problematizing review: a counterpoint to Elsbach and Van Knippenberg's argument for integrative reviews, J. Manag. Stud. 57 (6) (2020) 1290–1304, https://doi.org/10.1111/joms.12582.
[15] R. Dantu, I. Dissanayake, S. Nerur, Exploratory analysis of internet of things (IoT) in healthcare: a topic modelling & co-citation approaches, Inf. Syst. Manag. (2020) 1–17.
[16] G. Wagner, R. Lukyanenko, G. Paré, Artificial intelligence and the conduct of literature reviews, J. Inf. Technol. 37 (2) (2022) 209–226, https://doi.org/10.1177/02683962211048201.
[17] D.M. Blei, A.Y. Ng, M.I. Jordan, Latent dirichlet allocation, J. Mach. Learn. Res. 3 (Jan) (2003) 993–1022.
[18] Grootendorst, M. (2022). *BERTopic: Neural topic modeling with a class-based TF-IDF procedure* (No. arXiv:2203.05794). arXiv. http://arxiv.org/abs/2203.05794.
[19] R.J. Gallagher, K. Reing, D. Kale, G.V. Steeg, Anchored correlation explanation: topic modeling with minimal domain knowledge, Trans. Assoc. Comput. Linguist. 5 (0) (2017). Article 0.
[20] R.L. Ackoff, Towards a system of systems concepts, Manag. Sci. 17 (11) (1971) 661–671, https://doi.org/10.1287/mnsc.17.11.661.
[21] J.P. Van Gigch, Applied General Systems Theory, Harper & Row, 1978.
[22] C.W. Churchman, Perspectives of the systems approach, Interfaces. (Providence) 4 (4) (1974) 6–11.
[23] J. Howe, The rise of crowdsourcing, Wired (2006). https://www.wired.com/2006/06/crowds/.
[24] I. García, M.-N. Guillot, K. Zimányi, J. Langman, Book reviews, The Translator 18 (2) (2012) 373–392, https://doi.org/10.1080/13556509.2012.10799516.
[25] G.D. Saxton, O. Oh, R. Kishore, Rules of crowdsourcing: models, issues, and systems of control, Inf. Syst. Manag. 30 (1) (2013) 2–20, https://doi.org/10.1080/10580530.2013.739883.
[26] J. Mo, S. Sarkar, S. Menon, Know when to run: recommendations in crowdsourcing contests, MIS Q. 42 (3) (2018) 919–944.
[27] R. Lukyanenko, J. Parsons, Beyond micro-tasks: research opportunities in observational crowdsourcing, J. Database Manag. 29 (1) (2018) 1–22, https://doi.org/10.4018/JDM.2018010101.
[28] A. Wiggins, K. Crowston, From conservation to crowdsourcing: a typology of citizen science, in: 2011 44th Hawaii International Conference on System Sciences, 2011, pp. 1–10, https://doi.org/10.1109/HICSS.2011.207.
[29] R. Lenart-Gansiniec, Towards a typology development of crowdsourcing in science, J. Inf. Sci. (2022), https://doi.org/10.1177/01655515221118045, 01655515221118045.
[30] I. Pavlidou, S. Papagiannidis, E. Tsui, Crowdsourcing: a systematic review of the literature using text mining, Ind. Manag. Data Syst. 120 (11) (2020) 2041–2065, https://doi.org/10.1108/IMDS-08-2020-0474.
[31] B. Min, H. Ross, E. Sulem, A.P.B. Veyseh, T.H. Nguyen, O. Sainz, E. Agirre, I. Heintz, D. Roth, Recent advances in natural language processing via large pre-trained language models: a survey, ACM. Comput. Surv. 56 (2) (2023), https://doi.org/10.1145/3605943, 30:1-30:40.
[32] R. Lukyanenko, V.C. Storey, O. Pastor, System: a core conceptual modeling construct for capturing complexity, Data Knowl. Eng. 141 (2022) 102062, https://doi.org/10.1016/j.datak.2022.102062.
[33] H. Benbya, N. Nan, H. Tanriverdi, Y. Yoo, Complexity and information systems research in the emerging digital world, MIS Q. 44 (1) (2020). https://papers.ssrn.com/abstract=3539079.
[34] R.P. Bostrom, J.S. Heinen, MIS problems and failures: a socio-technical perspective. part I: the causes, MIS Q. 1 (3) (1977) 17–32, https://doi.org/10.2307/248710.
[35] S. Sarker, S. Chatterjee, X. Xiao, A. Elbanna, The sociotechnical axis of cohesion for the IS discipline: its historical legacy and its continued relevance, MIS Q. 43 (3) (2019) 695–720, https://doi.org/10.25300/MISQ/2019/13747.
[36] M.C.M. Lee, H. Scheepers, A.K.H. Lui, E.W.T. Ngai, The implementation of artificial intelligence in organizations: a systematic literature review, Inf. Manag. 60 (5) (2023) 103816, https://doi.org/10.1016/j.im.2023.103816.

[37] C.F. Lei, E.W.T. Ngai, Blockchain from the information systems perspective: literature review, synthesis, and directions for future research, Inf. Manag. 60 (7) (2023) 103856, https://doi.org/10.1016/j.im.2023.103856.
[38] Y. Wu, E.W.T. Ngai, P. Wu, C. Wu, Fake news on the internet: a literature review, synthesis and directions for future research, Internet Res. 32 (5) (2022) 1662–1699, https://doi.org/10.1108/INTR-05-2021-0294.
[39] D. Antons, C.F. Breidbach, A.M. Joshi, T.O. Salge, Computational literature reviews: method, algorithms, and roadmap, Organ. Res. Methods 26 (1) (2023) 107–138, https://doi.org/10.1177/1094428121991230.
[40] C.B. Asmussen, C. Møller, Smart literature review: a practical topic modelling approach to exploratory literature review, J. Big. Data 6 (1) (2019) 93, https://doi.org/10.1186/s40537-019-0255-7.
[41] K.R. Larsen, C.H. Bong, A tool for addressing construct identity in literature reviews and meta-analyses, MIS Q. 40 (3) (2016) 529–552.
[42] R. Egger, J. Yu, A topic modeling comparison between LDA, NMF, Top2Vec, and BERTopic to demystify twitter posts, Front. Sociol. 7 (2022), https://doi.org/10.3389/fsoc.2022.886498.
[43] Q. Fu, Y. Zhuang, J. Gu, Y. Zhu, X. Guo, Agreeing to disagree: choosing among eight topic-modeling methods, Big Data Res. 23 (2021) 100173, https://doi.org/10.1016/j.bdr.2020.100173.
[44] G. Paré, M.-C. Trudel, M. Jaana, S. Kitsiou, Synthesizing information systems knowledge: a typology of literature reviews, Inf. Manag. 52 (2015) 183–199, https://doi.org/10.1016/j.im.2014.08.008.
[45] D. Steininger, P. Mikalef, A. Pateli, A. Ortiz-de-Guinea, Dynamic capabilities in information systems research: a critical review, synthesis of current knowledge, and recommendations for future research, J. Assoc. Inf. Syst. 23 (2) (2022) 447–490, https://doi.org/10.17705/1jais.00736.
[46] A. Jeyaraj, A.H. Zadeh, Evolution of information systems research: Insights from topic modeling, Inf. Manag. 57 (4) (2020) 103207, https://doi.org/10.1016/j.im.2019.103207.
[47] K.K. Kapoor, K. Tamilmani, N.P. Rana, P. Patil, Y.K. Dwivedi, S. Nerur, Advances in social media research: past, present and future, Inf. Syst. Front. 20 (3) (2018) 531–558, https://doi.org/10.1007/s10796-017-9810-y.
[48] A. Sidorova, N. Evangelopoulos, J.S. Valacich, T. Ramakrishnan, Uncovering the intellectual core of the information systems discipline, MIS Q. 32 (3) (2008) 467–482, https://doi.org/10.2307/25148852.
[49] J. Cao, T. Xia, J. Li, Y. Zhang, S. Tang, A density-based method for adaptive LDA model selection, Neurocomputing. 72 (7) (2009) 1775–1781, https://doi.org/10.1016/j.neucom.2008.06.011.
[50] T.L. Griffiths, M. Steyvers, Finding scientific topics, Proc. Natl. Acad. Sci. 101 (suppl 1) (2004) 5228–5235, https://doi.org/10.1073/pnas.0307752101.
[51] P. Choudhury, D. Wang, N.A. Carlson, T. Khanna, Machine learning approaches to facial and text analysis: discovering CEO oral communication styles, Strateg. Manag. J. 40 (11) (2019) 1705–1732, https://doi.org/10.1002/smj.3067.
[52] P.O. Hoyer, Non-negative matrix factorization with sparseness constraints, J. Mach. Learn. Res. 5 (2004) 1457–1469.
[53] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A.N. Gomez, Ł. Kaiser, I. Polosukhin, Attention is all you need, in: Proceedings of the 31st International Conference on Neural Information Processing Systems, 2017, pp. 6000–6010.
[54] J. Devlin, M.-W. Chang, K. Lee, K. Toutanova, BERT: Pre-training of deep bidirectional transformers for language understanding, in: Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 2019, pp. 4171–4186, https://doi.org/10.18653/v1/N19-1423.
[55] A. Susarla, R. Gopal, J.B. Thatcher, S. Sarker, The Janus effect of generative AI: charting the path for responsible conduct of scholarly activities in information systems, Inf. Syst. Res. (2023), https://doi.org/10.1287/isre.2023.ed.v34.n2.
[56] I. Dissanayake, J. Zhang, M. Yasar, S.P. Nerur, Strategic effort allocation in online innovation tournaments, Inf. Manag. 55 (3) (2018) 396–406.
[57] Y. Jin, H.C.B. Lee, S. Ba, J. Stallaert, Winning by learning? Effect of knowledge sharing in crowdsourcing contests, Inf. Syst. Res. 32 (3) (2021) 836–859, https://doi.org/10.1287/isre.2020.0982.
[58] E. Segev, Crowdsourcing contests, Eur. J. Oper. Res. 281 (2) (2020) 241–255, https://doi.org/10.1016/j.ejor.2019.02.057.
[59] I. Dissanayake, N. Mehta, P. Palvia, V. Taras, K. Amoako-Gyampah, Competition matters! Self-efficacy, effort, and performance in crowdsourcing teams, Inf. Manag. 56 (8) (2019) 103158, https://doi.org/10.1016/j.im.2019.04.001.
[60] J. Mihm, J. Schlapp, Sourcing innovation: on feedback in contests, Manag. Sci. 65 (2) (2018) 559–576, https://doi.org/10.1287/mnsc.2017.2955.
[61] Y. Yang, P.-Y. Chen, P. Pavlou, Open innovation: an empirical study of online contests, in: ICIS 2009 Proceedings, 2009. https://aisel.aisnet.org/icis2009/13.
[62] H.C.B. Lee, S. Ba, X. Li, J. Stallaert, Salience bias in crowdsourcing contests, Inf. Syst. Res. 29 (2) (2018).
[63] I. Dissanayake, S. Nerur, J. Wang, M. Yasar, J. Zhang, The impact of helping others in coopetitive crowdsourcing communities, J. Assoc. Inf. Syst. 22 (1) (2021), https://doi.org/10.17705/1jais.00491.
[64] S. Zhang, P.V. Singh, A. Ghose, A structural analysis of the role of superstars in crowdsourcing contests, Inf. Syst. Res. 30 (1) (2019) 15–33, https://doi.org/10.1287/isre.2017.0767.
[65] T.X. Liu, J. Yang, L.A. Adamic, Y. Chen, Crowdsourcing with all-pay auctions: a field experiment on Taskcn, Manag. Sci. 60 (8) (2014) 2020–2037, https://doi.org/10.1287/mnsc.2013.1845.
[66] J. Huang, N. Duan, P. Ji, C. Ma, feng hu, Y. Ding, Y. Yu, Q. Zhou, W. Sun, A crowdsource-based sensing system for monitoring fine-grained air quality in urban environments, IEEe Internet. Things. J. 6 (2) (2019) 3240–3247, https://doi.org/10.1109/JIOT.2018.2881240. IEEE Internet of Things Journal.
[67] X. Deng, K.D. Joshi, R.D. Galliers, The duality of empowerment and marginalization in microtask crowdsourcing: giving voice to the less powerful through value sensitive design, MIS Q. 40 (2) (2016), 279-A19.
[68] D. Durward, I. Blohm, J.M. Leimeister, The Nature of crowd work and its effects on individuals' work perception, J. Manag. Inf. Syst. 37 (1) (2020) 66–95, https://doi.org/10.1080/07421222.2019.1705506.
[69] X.(Nancy) Deng, K.D. Joshi, Is Crowdsourcing a source of worker empowerment or exploitation? Understanding crowd workers' perceptions of crowdsourcing career, in: ICIS 2013 Proceedings, 2013, in: https://aisel.aisnet.org/icis2013/proceedings/ResearchInProgress/33.
[70] S. Moussawi, M. Koufaris, Working on low-paid micro-task crowdsourcing platforms: an existence, relatedness and growth view, in: ICIS 2015 Proceedings, 2015, in: https://aisel.aisnet.org/icis2015/proceedings/HumanBehaviorIS/15.
[71] D. Kost, C. Fieseler, S.I. Wong, Finding meaning in a hopeless place? The construction of meaningfulness in digital microwork, Comput. Human. Behav. 82 (2018) 101–110, https://doi.org/10.1016/j.chb.2018.01.002.
[72] D. Schlagwein, D. Cecez-Kecmanovic, B. Hanckel, Ethical norms and issues in crowdsourcing practices: a Habermasian analysis, Inf. Syst. J. 29 (4) (2019) 811–837, https://doi.org/10.1111/isj.12227.
[73] A.M. Brawley, C.L.S. Pury, Work experiences on MTurk: job satisfaction, turnover, and information sharing, Comput. Human. Behav. 54 (2016) 531–546, https://doi.org/10.1016/j.chb.2015.08.031.
[74] X. Ma, L. Khansa, S.S. Kim, Active community participation and crowdworking turnover: a longitudinal model and empirical test of three mechanisms, J. Manag. Inf. Syst. 35 (4) (2018) 1154–1187, https://doi.org/10.1080/07421222.2018.1523587.
[75] L. Schmidt, F. Dost, E. Maier, Filtering survey responses from crowdsourcing platforms: current heuristics and alternative approaches, in: ICIS 2019 Proceedings, 2019. https://aisel.aisnet.org/icis2019/research_methods/research_methods/8.
[76] Z.R. Steelman, B.I. Hammer, M. Limayem, Data collection in the digital age: innovative alternatives to student samples, MIS Q. 38 (2) (2014) 355–378.
[77] R. Jia, Z.R. Steelman, B.H. Reich, Using mechanical turk data in IS research: risks, rewards, and recommendations, Commun. Assoc. Inf. Syst. 41 (2017) 14, https://doi.org/10.17705/1CAIS.04114.
[78] J. Wang, P.G. Ipeirotis, F. Provost, Cost-effective quality assurance in crowd labeling, Inf. Syst. Res. 28 (1) (2017) 137–158, https://doi.org/10.1287/isre.2016.0661.
[79] E. Brynjolfsson, T. Geva, S. Reichman, Crowd-squared: amplifying the predictive power of search trend data, MIS Q. 40 (4) (2016) 941–962.
[80] Y. Huang, P.V. Singh, K. Srinivasan, Crowdsourcing new product ideas under consumer learning, Manag. Sci. 60 (9) (2014) 2138–2159.
[81] D.W. Dahl, C. Fuchs, M. Schreier, Why and when consumers prefer products of user-driven firms: a social identification account, Manag. Sci. 61 (8) (2014) 1978–1988, https://doi.org/10.1287/mnsc.2014.1999.
[82] B.L. Bayus, Crowdsourcing new product ideas over time: an analysis of the dell ideastorm community, Manag. Sci. 59 (1) (2013) 226–244.
[83] Q. Liu, Q. Du, Y. Hong, W. Fan, S. Wu, User idea implementation in open innovation communities: evidence from a new product development crowdsourcing community, Inf. Syst. J. 30 (5) (2020) 899–927, https://doi.org/10.1111/isj.12286.
[84] M.K. Poetz, M. Schreier, The value of crowdsourcing: can users really compete with professionals in generating new product ideas? J. Prod. Innov. Manag. 29 (2) (2012) 245–256, https://doi.org/10.1111/j.1540-5885.2011.00893.x.
[85] E.H. Hwang, P.V. Singh, L. Argote, Jack of all, master of some: information network and innovation in crowdsourcing communities, Inf. Syst. Res. 30 (2) (2019) 389–410, https://doi.org/10.1287/isre.2018.0804.
[86] I. Blohm, C. Riedl, J. Füller, J.M. Leimeister, Rate or trade? Identifying winning ideas in open idea sourcing, Inf. Syst. Res. 27 (1) (2016) 27–48, https://doi.org/10.1287/isre.2015.0605.
[87] D.E. O'Leary, On the relationship between number of votes and sentiment in crowdsourcing ideas and comments for innovation: a case study of Canada's digital compass, Decis. Support. Syst. 88 (2016) 28–37, https://doi.org/10.1016/j.dss.2016.05.006.
[88] J.M. Leimeister, M. Huber, U. Bretschneider, H. Krcmar, Leveraging crowdsourcing: activation-supporting components for IT-based ideas competition, J. Manag. Inf. Syst. 26 (1) (2009) 197–224.
[89] H. Piezunka, L. Dahlander, Idea rejected, tie formed: organizations' feedback on crowdsourced ideas, Acad. Manag. J. 62 (2) (2019) 503–530, https://doi.org/10.5465/amj.2016.0703.
[90] J.O. Wooten, K.T. Ulrich, Idea generation and the role of feedback: evidence from field experiments with innovation tournaments, Prod. Oper. Manag. 26 (1) (2017) 80–99, https://doi.org/10.1111/poms.12613.
[91] T.K. Koh, Adopting seekers' solution exemplars in crowdsourcing ideation contests: antecedents and consequences, Inf. Syst. Res. 30 (2) (2019) 486–506, https://doi.org/10.1287/isre.2018.0810.
[92] C. Yin, C. Jiang, H.K. Jain, Y. Liu, B. Chen, Capturing product/service improvement ideas from social media based on lead user theory, J. Prod. Innov. Manag. 40 (5) (2023) 630–656, https://doi.org/10.1111/jpim.12676.
[93] N. van Berkel, J. Goncalves, K. Wac, S. Hosio, A.L. Cox, Human accuracy in mobile data collection, Int. J. Hum. Comput. Stud. 137 (2020) 102396, https://doi.org/10.1016/j.ijhcs.2020.102396.
[94] R. Bonney, C.B. Cooper, J. Dickinson, S. Kelling, T. Phillips, K.V. Rosenberg, J. Shirk, Citizen science: a developing tool for expanding science knowledge and scientific literacy, Bioscience 59 (11) (2009) 977–984, https://doi.org/10.1525/bio.2009.59.11.9.

[95] C. Cooper, Citizen Science: How Ordinary People are Changing the Face of Discovery, Abrams, 2016.
[96] M. Levy, M. Germonprez, The potential for citizen science in information systems research, Commun. Assoc. Inf. Syst. 40 (1) (2017), https://doi.org/10.17705/1CAIS.04002.
[97] J.M. Robson, A.A. Green, Closing the loop on crowdsourced science, Proc. Natl. Acad. Sci. 119 (25) (2022) e2205897119, https://doi.org/10.1073/pnas.2205897119.
[98] M. Poblet, E. García-Cuesta, P. Casanovas, Crowdsourcing roles, methods and tools for data-intensive disaster management, Inf. Syst. Front. 20 (6) (2018) 1363–1379, https://doi.org/10.1007/s10796-017-9734-6.
[99] A. Komninos, Pro-social behaviour in crowdsourcing systems: experiences from a field deployment for beach monitoring, Int. J. Hum. Comput. Stud. 124 (2019) 93–115, https://doi.org/10.1016/j.ijhcs.2018.12.001.
[100] V. Benjamin, T.S. Raghu, Augmenting social bot detection with crowd-generated labels, Inf. Syst. Res. (2022), https://doi.org/10.1287/isre.2022.1136.
[101] R. Lukyanenko, J. Parsons, Y.F. Wiersma, The IQ of the crowd: understanding and improving information quality in structured user-generated content, Inf. Syst. Res. 25 (4) (2014) 669–689, https://doi.org/10.1287/isre.2014.0537.
[102] A. Richter, O. Comay, C.S. Svenningsen, J.C. Larsen, S. Hecker, A.P. Tøttrup, G. Pe'er, R.R. Dunn, A. Bonn, M. Marselle, Motivation and support services in citizen science insect monitoring: a cross-country study, Biol. Conserv. 263 (2021) 109325, https://doi.org/10.1016/j.biocon.2021.109325.
[103] D. Rotman, J. Preece, J. Hammock, K. Procita, D. Hansen, C. Parr, D. Lewis, D. Jacobs, Dynamic changes in motivation in collaborative citizen-science projects, in: Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work, 2012, pp. 217–226, https://doi.org/10.1145/2145204.2145238.
[104] R. Lukyanenko, Citizen Science 3.0: a vision for the future of digital citizen science, in: Proceedings of International Conferenze on IT e Computer Science (ICITCS–2019). London, 2019.
[105] R. Lukyanenko, J. Parsons, Y. Wiersma, G. Wachinger, B. Huber, R. Meldt, Representing crowd knowledge: guidelines for conceptual modeling of user-generated content, J. Assoc. Inf. Syst. 18 (4) (2017), https://doi.org/10.17705/1jais.00456.
[106] H.(Jonathan) Ye, A. Kankanhalli, Investigating the antecedents of organizational task crowdsourcing, Inf. Manag. 52 (1) (2015) 98–110, https://doi.org/10.1016/j.im.2014.10.007.
[107] I. Dissanayake, S. Nerur, R. Singh, Y. Lee, Medical crowdsourcing: harnessing the "wisdom of the crowd" to solve medical mysteries, J. Assoc. Inf. Syst. 20 (11) (2019), https://doi.org/10.17705/1jais.00579.
[108] A. Afuah, C.L. Tucci, Crowdsourcing as a solution to distant search, Acad. Manag. Rev. 37 (3) (2012) 355–375.
[109] M. Hvalshagen, R. Lukyanenko, B.M. Samuel, Empowering users with narratives: examining the efficacy of narratives for understanding data-oriented conceptual models, Inf. Syst. Res. (2022), https://doi.org/10.1287/isre.2022.1141.
[110] H. Zheng, D. Li, W. Hou, Task design, motivation, and participation in crowdsourcing contests, Int. J. Electron. Commer. 15 (4) (2011) 57–88.
[111] X.(Nancy) Deng, K.D. Joshi, Why individuals participate in micro-task crowdsourcing work environment: revealing crowdworkers' perceptions, J. Assoc. Inf. Syst. 17 (10) (2016), https://doi.org/10.17705/1jais.00441.
[112] J. Taylor, K.d. Joshi, Joining the crowd: the career anchors of information technology workers participating in crowdsourcing, Inf. Syst. J. 29 (3) (2019) 641–673, https://doi.org/10.1111/isj.12225.
[113] J. Bauer, N. Franke, P. Tuertscher, Intellectual property norms in online communities: how user-organized intellectual property regulation supports innovation, Inf. Syst. Res. 27 (4) (2016) 724–750, https://doi.org/10.1287/isre.2016.0649.
[114] C. Fieseler, E. Bucher, C.P. Hoffmann, Unfairness by design? The perceived fairness of digital labor on crowdworking platforms, J. Bus. Ethics 156 (4) (2019) 987–1005, https://doi.org/10.1007/s10551-017-3607-2.
[115] M. Wang, X. Cui, The role of rating feedback and its implications for solver submission behavior in crowdsourcing contests, Inf. Manag. (2023) 103790, https://doi.org/10.1016/j.im.2023.103790.
[116] S.I. Wong, A. Bunjak, M. Černe, C. Fieseler, Fostering creative performance of platform crowdworkers: the digital feedback dilemma, Int. J. Electron. Commer. 25 (3) (2021) 263–286, https://doi.org/10.1080/10864415.2021.1942674.
[117] D.L. Dean, J. Hender, T. Rodgers, E. Santanen, Identifying good ideas: constructs and scales for idea evaluation, J. Assoc. Inf. Syst. 7 (10) (2006) 646–699.
[118] J. Love, R. Hirschheim, Crowdsourcing of information systems research, Eur. J. Inf. Syst. 26 (3) (2017) 315–332, https://doi.org/10.1057/s41303-017-0036-3.
[119] A. Majchrzak, A. Malhotra, Towards an information systems perspective and research agenda on crowdsourcing for innovation, J. Strateg. Inf. Syst. 22 (4) (2013) 257–268, https://doi.org/10.1016/j.jsis.2013.07.004.
[120] R. Lukyanenko, A. Wiggins, H.K. Rosser, Citizen science: an information quality research frontier, Inf. Syst. Front. 22 (4) (2020) 961–983, https://doi.org/10.1007/s10796-019-09915-z.
[121] A. Castellanos, M. Tremblay, R. Lukyanenko, B. Samuel, Basic classes in conceptual modeling: theory and practical guidelines, J. Assoc. Inf. Syst. 21 (4) (2020), https://doi.org/10.17705/1jais.00627.
[122] I. Dissanayake, J. Zhang, B. Gu, Task division for team success in crowdsourcing contests: resource allocation and alignment effects, J. Manag. Inf. Syst. 32 (2) (2015) 8–39.
[123] I. Dissanayake, S. Nerur, J. Zhang, Team Formation and performance in online crowdsourcing competitions: the role of homophily and diversity in solver characteristics, in: ICIS 2019 Proceedings, 2019. https://aisel.aisnet.org/icis2019/crowds_social/crowds_social/5.
[124] A. Elbanna, A. Idowu, Crowdwork, digital liminality and the enactment of culturally recognised alternatives to western precarity: beyond epistemological terra nullius, Eur. J. Inf. Syst. 0 (0) (2021) 1–17, https://doi.org/10.1080/0960085X.2021.1981779.
[125] X. Ma, L. Khansa, J. Hou, Toward a contextual theory of turnover intention in online crowdworking, in: ICIS 2016 Proceedings, 2016. https://aisel.aisnet.org/icis2016/HumanBehavior/Presentations/3.
[126] L. Jiang, C. Wagner, X. Chen, Taking time into account: understanding microworkers' continued participation in microtasks, J. Assoc. Inf. Syst. 22 (4) (2021), https://doi.org/10.17705/1jais.00684.
[127] S.L. Alam, J. Campbell, Temporal motivations of volunteers to participate in cultural crowdsourcing work, Inf. Syst. Res. 28 (4) (2017) 744–759, https://doi.org/10.1287/isre.2017.0719.
[128] L. Von Bertalanffy, An outline of general system theory, Br. J. Philos. Sci. 1 (1950) 134–165, https://doi.org/10.1093/bjps/I.2.134.
[129] M. Lysyakov, S. Viswanathan, Threatened by AI: analyzing users' responses to the introduction of AI in a crowd-sourcing platform, Inf. Syst. Res. 34 (3) (2023) 1191–1210, https://doi.org/10.1287/isre.2022.1184.
[130] M. Greineder, I. Blohm, Transforming work organization with internal crowds: a process theory, in: ICIS 2020 Proceedings, 2020. https://aisel.aisnet.org/icis2020/sharing_economy/sharing_economy/14.

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