

The Relationship Between Persuasion Cues and Idea Adoption in Virtual Crowdsourcing Communities: Evidence From a Business Analytics Community

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ABSTRACT

Building on the elaboration likelihood model (ELM) and absorptive capacity, this study develops a four-dimensional model of idea adoption in virtual crowdsourcing communities (VCCs) and examines the influence of different persuasion cues on idea adoption. The research model was tested using hierarchical logistic regression based on a dataset from the Tableau community. The results show that both community recognition of users and community recognition of ideas are positively related to idea adoption. Proactive user engagement has a significant positive impact on idea adoption, while reactive user engagement has no significant impact. Idea content quality, represented by idea length and supporting arguments, has an inverted U-shaped relationship with idea adoption. Community absorptive capacity positively moderates the curvilinear relationship between idea content quality and idea adoption. These results contribute to a better elucidation of the persuasion mechanisms underlying idea adoption in VCCs and thus provide important implications for open innovation research and practice.

KEYWORDS

Absorptive Capacity (AC), Business Intelligence and Analytics (BI&A), Elaboration Likelihood Model (ELM), Idea Adoption, Tableau Software, Virtual Crowdsourcing Communities (VCCs)

1. INTRODUCTION

With the rapidly growing number and capabilities of digital innovation channels, and the increasing scale and complexity of user requirements and preferences, internal innovation models are increasingly being superseded by open innovation models that leverage “purposeful inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively” (Chesbrough, 2019). The manifestation of this evolution of innovation sourcing models, typically hosted over the Internet, is commonly referred to as virtual crowdsourcing communities (VCCs) (Saez-Rodriguez et al., 2016). In essence, a VCC provides an arena that allows a heterogeneous set of online users to collectively participate in the innovation process and generate a wealth of creative ideas that can be transformed into new and profitable products, services, or business models (Luo, Lan, Luo, & Li, 2021). The literature has already emphasized the importance of VCCs in streamlining innovation efforts, bringing new and improved products to market and, most importantly, mitigating potential inefficiencies in the internal innovation process by outsourcing idea generation and evaluation

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to online crowds (Lipusch, Dellermann, Bretschneider, Ebel, & Leimeister, 2020; Q. Liu, Du, Hong, Fan, & Wu, 2020; Ma, Lu, & Gupta, 2019; Medase & Barasa, 2019; Qin & Liang, 2019). As a result, VCCs are increasingly viewed as a critical source of sustainable competitive intelligence due to their ability to elicit collective knowledge that is both novel, i.e., original or unexpected, and valuable, i.e., applicable and relevant to user needs and preferences (Akman, Plewa, & Conduit, 2019; Romero & Molina, 2009). Recognizing their valuable contribution to the development of innovation and entrepreneurship, a growing number of companies such as Microsoft, Tableau, and Google have established their own VCCs and focused on how to motivate users to contribute ideas and innovation solutions to their communities (Olmedilla, Send, & Toral, 2019). In all of these cases, community hosting companies seek to provide a collaborative innovation environment to foster creativity and facilitate online communication between companies and their customers for crowdsourced ideas, and then use these insights to better implement innovation-driven development strategies and improve internal research and development (R&D) capabilities (Q. Liu et al., 2020; F. Wang, Zhao, Chi, & Li, 2017).

While VCCs have increasingly become an important source for soliciting a wealth of creative ideas, one of the biggest challenges for companies is identifying high-quality ideas that can be adopted and developed into successful innovations, while excluding low-quality ideas to avoid investing limited resources in them (Cheng et al., 2020; Olmedilla et al., 2019). In practice, organizations face significant challenges in encouraging active user participation in innovation crowdsourcing, managing and monitoring community activities (Haeffliger et al., 2011), and soliciting feedback on their new products and services (Troise, Matricano, & Sorrentino, 2020). Part of the paradox is that the volume of useful, voluntarily generated ideas from the online crowd continues to grow, while organizational resources to support the identification, convergence, and adoption of high-quality ideas are typically limited (Cheng et al., 2020). Additionally, many companies lack clearly defined criteria for evaluating submitted ideas, and are often constrained by limited human resources and systematic procedures for evaluating the growing number of ideas submitted (Tsou & Chen, 2020; von Helversen, Abramczuk, Kopeć, & Nielek, 2018; F. Wang et al., 2017). Conversely, it is difficult for community users to convince companies to adopt their ideas after they have invested significant time and intellectual resources in developing them. Since the percentage of high-quality ideas that are ultimately adopted is typically low, users are keen to learn how they can increase the likelihood that their ideas and innovations will be disseminated and adopted by community operators. As ideas continue to flow and contributors become diverse, there are problems such as low-quality contributions, ambiguous or nonstandard elaborations, and a lack of serial focus on a particular topic; this leads to a critical phenomenon of information redundancy and cognitive overload (Yan, Leidner, & Benbya, 2018). Furthermore, community adoption of ideas is a time-consuming and lengthy process that requires significant effort to organize, filter, and evaluate ideas and feedback from multiple users (Cheng et al., 2020). Therefore, understanding the mechanisms underlying idea adoption and helping communities quickly identify high-quality ideas from the rich stream of crowd-generated ideas is critical to achieving fruitful innovation outcomes and fostering co-innovation capabilities in organizations (F. Wang et al., 2017).

The extant research on VCCs has largely focused on investigating how online crowds can be motivated to contribute new ideas and collaborate on proposals in an integrated innovation process (Caccamo, 2020; Chesbrough & Bogers, 2014; Yang & Han, 2019; Yu & Liu, 2020; Zhou, 2011). Previous studies have also examined decision-making processes in crowdsourcing communities and found that the content quality and creativity of ideas submitted are key determinants of successful prioritization and idea adoption (Nevo & Kotlarsky, 2020). Nevertheless, a number of research gaps remain in the literature. First, previous studies have examined various idea characteristics that may influence idea adoption decisions (e.g., Gerlach & Brem, 2017; Globocnik & Faillant, 2020; Hoornaert, Ballings, Malthouse, & Van den Poel, 2017; Hossain & Islam, 2015b; Hu, Xu, & Wang, 2020). However, little attention has been paid to the underlying mechanisms through which online

persuasion cues influence idea evaluation, prioritization, and adoption. Second, one of the main challenges for VCCs is that they accumulate a wealth of ideas and online reviews that can easily overwhelm the receptivity of the community (Martínez-Torres, Rodríguez-Piñero, & Toral, 2015; Martínez-Torres & Olmedilla, 2016). Typically, crowd-generated ideas and feedback should be evaluated individually by the company's innovation department or by dedicated experts to assess their feasibility and application potential. Therefore, an empirical investigation of the relationship between the community's absorptive capacity and the likelihood of idea adoption is crucial, as companies are usually equipped with different capacities and resources to absorb, identify, process and use innovative ideas to create value (Hoornaert et al., 2017; Medase & Barasa, 2019). Third, the process of idea adoption in VCCs has been investigated in a growing number of studies (Akman et al., 2019; Qin & Liang, 2019). However, because the process of idea adoption involves a sequence of persuasion activities and is influenced by a variety of factors, a more holistic approach to studying the determinants of idea adoption in VCCs must include a clear understanding of both idea characteristics and actor characteristics. At the same time, the underlying mechanisms by which preferences and/or behaviors of community members reinforce, modify, or shape the process of persuasion and idea adoption merit further research (Allison, Davis, Webb, & Short, 2017; Yang & Han, 2019).

The above practical and theoretical challenges motivate this study to holistically examine the antecedents of idea adoption in VCCs by incorporating both the characteristics of ideas and contributors and the mechanisms by which ideas and associated content are acquired, vetted, and ultimately prioritized for adoption. Specifically, this study aims to develop a theoretical understanding of how persuasion processes (routes) and cues influence the decision to adopt ideas in VCCs, and thus the outcomes of innovation crowdsourcing ventures. Typically, VCCs are characterized by low review capacity; i.e., there are insufficient human resources for in-depth evaluation of the numerous user ideas submitted daily on various topics (M. Li, Kankanhalli, & Kim, 2016; Q. Liu et al., 2020). Therefore, this study postulates that user-generated ideas are likely to be considered for adoption if they are persuasive, properly framed, and elaborated on the community, while at the same time the submitted content does not exceed the absorptive capacity of both community reviewers and other community members. In light of this argument, this study draws on the elaboration likelihood model (ELM) of persuasion (Petty, Kasmer, Haugtvedt, & Cacioppo, 1987) and community absorptive capacity (Cohen & Levinthal, 1990) to develop a four-dimensional model to explain the likelihood of idea adoption in VCCs. Through this model, this study aims to investigate how different determinants, constituting different online persuasion cues, influence idea adoption at both individual and community levels. The research model and hypotheses were examined using hierarchical logistic regression based on a data sample of 9297 crowd-generated ideas collected from the Tableau Community (<https://community.tableau.com/s/ideas>); an online idea crowdsourcing community created specifically to solicit innovation ideas and solutions from business intelligence and analytics practitioners and business users.

This study makes a threefold contribution to the current stream of research on innovation crowdsourcing and BI&A virtual communities. First, it supports previous studies on the idea crowdsourcing process by showing that community recognition of users, community recognition of ideas, proactive user engagement and contributions, and idea content quality are positively related to idea adoption in VCCs. Second, it complements this line of research by examining how community absorptive capacity positively moderates the relationship between idea content quality and idea adoption. Finally, it extends the applicability of ELM and absorptive capacity to the context of online innovation crowdsourcing and provides a theoretical lens for other researchers to further explore the antecedents of idea adoption in the innovation context of BI&A (Yang & Han, 2019). It is worth noting that this study examines idea adoption as a direct outcome of the innovation process, rather than the actual implementation of the idea in the form of a new product or service, as this represents the early stage of the innovation process and the primary goal of VCCs. From a practical perspective, the results of this study should not only serve as a guide for companies seeking to increase their

capacity to embrace innovation, but also help online crowds articulate their innovation ideas in a way that increases the likelihood of their adoption.

The remainder of this article is organized as follows. Section 2 provides a literature review of key concepts and theoretical considerations. Section 3 discusses the development of the research model and hypotheses. Section 4 describes the research methodology, including the constructs, related measures, and data collection procedure used in the study. Section 5 presents the data analysis and results of the study. Section 6 discusses the findings and their implications for research and practice. Section 7 discusses the limitations of this study, followed by an overall conclusion in Section 8.

2. THEORETICAL BACKGROUND

2.1 Idea Adoption in Crowdsourcing Communities

The concept of crowdsourcing refers to the process of outsourcing innovation activities, mainly performed within an organization, to a large, heterogeneous and rapidly evolving crowd of users and external actors (Hossain & Kauranen, 2015). The innovation crowdsourcing process aims to effectively leverage individuals or organizations for innovative solutions and ideas (Vianna, Graeml, & Peinado, 2020). Enabled by Internet and Web 2.0 technologies, VCCs present themselves as a key enabler of collective intelligence and collaborative knowledge creation, manifested in synergies, exchanges, and contests among multiple participants to generate innovative solutions and ideas (Akar & Mardikyan, 2018). Members collaborating in the ideation process are generally like-minded individuals who share common goals/interests and participate in co-creative activities that develop by building virtual relationships and breaking down barriers between individuals with different skills and knowledge backgrounds (Chesbrough, 2019). Therefore, VCCs can generally be used to strengthen the connectedness between products and their customers, as well as between customers themselves (Yan et al., 2018). Although VCCs are not necessarily created with collaborative innovation in mind, collaborative innovation can emerge and develop naturally during the course of community activities through sharing consumer experiences, addressing product-related problems, proposing solutions to potential difficulties, facilitating learning or teaching product use, and sharing or evaluating new ideas (Kruft, Tilsner, Schindler, & Kock, 2019).

Notwithstanding the diversity of conceptualizations for VCCs, a common theme that has been maintained is the outsourcing of problems to the crowd of users and an open call for contributions and innovation ideas to solve specific problems (Hossain & Kauranen, 2015). As an intermediary mechanism, innovation crowdsourcing is also characterized by voluntary participation, often without central hierarchical authority. Nevertheless, community members are expected to actively participate in a number of activities, including defining the specifications of the products to be developed, testing the products before their release, crowd voting on the final products, posting feedback/comments, or searching for new sources of innovation (Munir, Linåker, Wnuk, Runeson, & Regnell, 2018; Najafi-Tavani, Najafi-Tavani, Naudé, Oghazi, & Zeinaloo, 2018; Nevo & Kotlarsky, 2020). Alongside these activities, Kruft et al. (2019) argue that the outcome of innovation ideas posted in VCCs is influenced not only by their quality, but also by the interaction between crowd members around the ideas and the elaboration and presentation of the ideas in the community. In practice, crowd members are more likely to be influenced by the behavior of other members as they interact with ideas, share experiences, and formulate opinions (Haas, Criscuolo, & George, 2015; Yang & Han, 2019). While such collaboration activities are frequently discussed in the literature, their persuasive influence on idea adoption in VCCs has not been sufficiently empirically studied (Kruft et al., 2019).

The extant research on idea adoption in VCCs has generally focused on three main categories: idea content, idea generator, and evaluation feedback, while few studies have paid sufficient attention to the persuasion cues and mechanisms that drive decisions and behaviors related to idea convergence, evaluation, and adoption. Most previous studies have mainly focused on exploring and analyzing the

common characteristics of crowd-generated ideas to develop theory-based models for predicting idea adoption (Ho-Dac, 2020; Hossain & Islam, 2015a; Hu et al., 2020; Lipusch et al., 2020; Q. Liu et al., 2020; X. Liu, Wang, Fan, & Zhang, 2020). Related studies in this area make important contributions to collaborative innovation practices by helping organizations to efficiently and effectively process ideas in VCCs. The impact of adopting different types of human roles (e.g., lead user and employee involvement) on innovation creation has also been investigated in previous research (Martinez-Torres & Olmedilla, 2016; Rodriguez-Ricardo, Sicilia, & López, 2018; Yan et al., 2018; Yu & Liu, 2020; Zhou, 2011). In terms of idea characteristics, several studies have found that idea title length (Q. Liu et al., 2020), content length (Di Vincenzo, Mascia, Björk, & Magnusson, 2020), and novelty level (Qin & Liang, 2019; Troise et al., 2020) are significantly related to idea adoption. In addition, a growing body of research has shown that the inclusion of unstructured graphics, videos, and other arguments has a positive impact on idea quality (M. Li et al., 2016). Idea quality also depends on users' domain knowledge and innovation background. Recent studies have also examined user behavior and interaction in VCCs (Di Vincenzo et al., 2020; Olmedilla et al., 2019). In terms of evaluation feedback, previous studies (Kruft et al., 2019; Priharsari, Abedin, & Mastio, 2020; Saez-Rodriguez et al., 2016) have shown that idea ratings and associated scores can predict the likelihood of idea adoption. In addition, sentiment analysis of user reviews has shown that the number of positive reviews is positively related to idea quality, endorsement, and subsequent adoption in VCCs (Antons, Grünwald, Cichy, & Salge, 2020; Q. Liu et al., 2020; X. Liu et al., 2020; T. Wang, Wang, & Qi, 2018).

Several recent empirical studies have examined different theories to explain the determinants of idea adoption in VCCs. For example, the diffusion of innovations (DOI) theory, first introduced by Rogers (2003), has been used to examine how user behavior influences idea adoption in online idea crowdsourcing platforms. Researchers have also addressed user behavior during participation in idea crowdsourcing platforms as a knowledge cultivation process that can positively contribute to improving idea adoption (Devece, Palacios, & Ribeiro-Navarrete, 2019). For example, Hossain and Islam (2015b) conducted an empirical study using data from IdeaStorm and found that prior success experiences were positively associated with idea adoption. Drawing on cognitive load theory (CLT) (Leppink & van den Heuvel, 2015; Nonaka, 1994), Cheng et al. (2020) also showed that germinal cognitive load positively influences the process of filtering, reducing, and adopting ideas, while both intrinsic cognitive load and extrinsic cognitive load negatively correlate with the process of idea convergence and adoption. Similarly, Yan et al. (2018) applied CLT to study the interaction of individuals in VCCs and showed that knowledge and information sharing between collaborators and product users has a significant impact on the idea crowdsourcing process. Di Vincenzo et al. (2020) applied attention theory (Ocasio, 2011) to investigate how idea appreciation (i.e., positive feedback and comments posted on ideas) and idea attention (i.e., the number of contributors involved in the crowdsourcing process) are positively related to idea adoption in VCCs. The Actor network theory (ANT) and service logic were also applied to examine the relationship between user network proximity and idea adoption (Akman et al., 2019). Mack and Landau (2020) applied the component theory of creativity (CTC) (Amabile & Pillemer, 2012) to demonstrate that individual characteristics (i.e., domain knowledge, creativity processes, and task motivation) have a positive influence on ideas that represent incremental innovations and a negative influence on ideas that represent radical innovations. Collectively, these theoretical models reinforce the extent to which the likelihood of idea adoption is influenced by both ideation and elaboration characteristics of idea creators and submitted ideas. However, the mechanisms through which ideas and related content are processed, elaborated, and incorporated, and how these mechanisms influence idea adoption in the context of VCCs, remain poorly understood. Given that innovation crowdsourcing involves the engagement and stimulation of individuals to interact and collaborate and follows a sequence of persuasion activities that lead to the filtering, prioritization, and selection of ideas for further consideration, the elaboration likelihood model (ELM) arguably holds untapped potential to explain the phenomenon of idea adoption in VCCs.

2.2 Elaboration Likelihood Model

The elaboration likelihood model (ELM) (Petty & Cacioppo, 1986) is a dual process theory that attempts to explain the mechanisms (routes) through which the community and information contained in the community are evaluated, absorbed, and consumed by individuals. The basic premise of ELM is that individuals process information through two routes: the central route and the peripheral route. The central route is based on a detailed evaluation of the information contained in the community. In contrast, the peripheral route is based on a less detailed assessment of communicated information and instead tends to form judgments by relying on perceived peripheral cues such as supporting evidence and evaluation of ideas (Petty et al., 1987). The extent to which individuals choose one route over another is based on their state of elaboration likelihood and level of motivation (Allison et al., 2017; Cyr, Head, Lim, & Stibe, 2018). When individuals follow the central route, they are expected to exert high motivation and considerable cognitive effort to process the information, evaluate its content, and integrate other supporting arguments related to the information. The peripheral route, on the other hand, requires a lower level of motivation and cognitive effort to process information than the central route. Instead of thoughtful consideration or mental processing of information, the peripheral route relies on processing various heuristics and attractions associated with the information source (Cyr et al., 2018; Kitchen, Kerr, Schultz, McColl, & Pals, 2014).

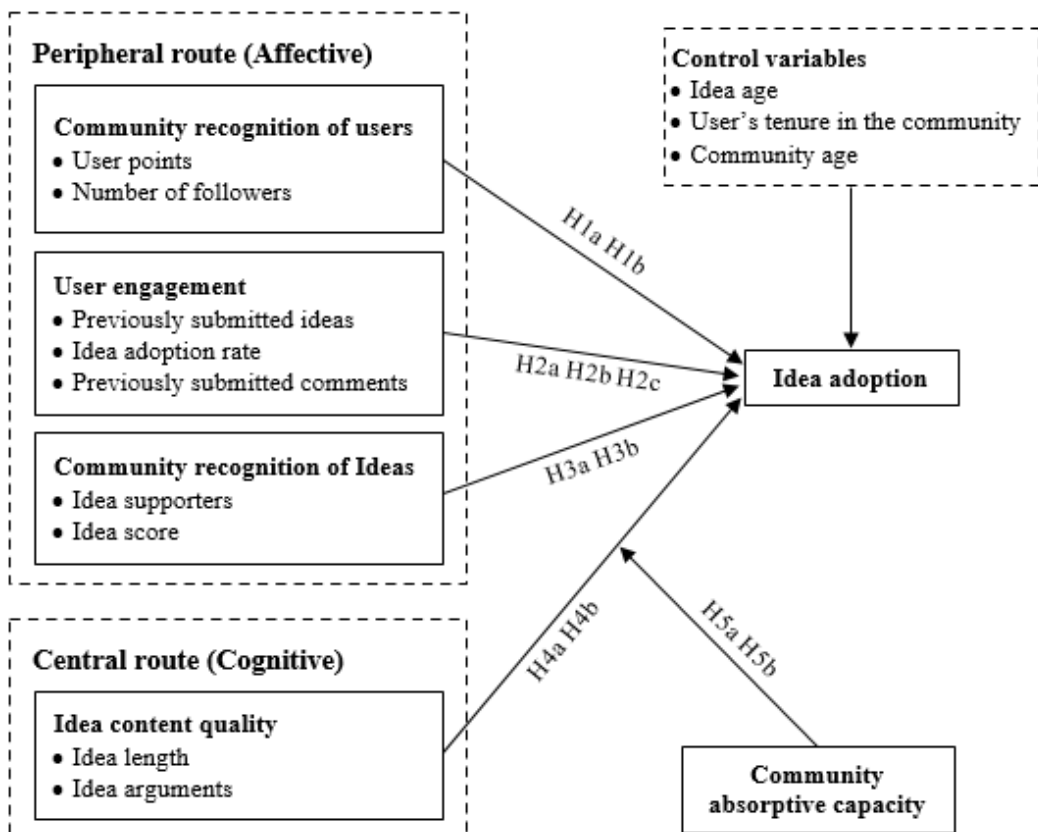
In the context of VCCs, the ELM suggests that idea adoption is a decision process that follows a sequence of persuasion activities, and the way these activities are structured and interconnected plays an important role in the process of idea adoption (Kruft et al., 2019). Arguably, these activities can be influenced by the perceived quality of the arguments associated with the idea-relevant information, presence of affective cues in the idea (Allison et al., 2017), variations in the underlying sentiment of the idea (Q. Liu et al., 2020), or even the perceived credibility of the idea source (Lee, Han, & Suh, 2018; C. Li, Zhang, & Han, 2021). Furthermore, crowd member behavior tends to influence how individuals in the crowd interact with ideas and what persuasions they form (Olmedilla et al., 2019). When applying ELM to VCCs, idea-relevant information typically consists of credible, tangible cues that directly relate to the content and quality of the idea, while peripheral cues represent the supporting elements associated with the idea (C. Li et al., 2021). For example, when evaluating an idea for a new product, persuasion via the central route can be aided by the availability of sound, fact-based arguments such as known or tested features and/or capabilities of a product (Lee et al., 2018). Community reviewers can use the peripheral route of ideas (information source) to guide heuristic thinking and then evaluate the central route of information (quality of supporting arguments) to ultimately make adoption decisions (Bhattacharjee & Sanford, 2006; Bi, Liu, & Usman, 2017). Therefore, the ELM of persuasion is particularly relevant and provides a theoretical lens for the systematic analysis of the idea adoption process in VCCs. As idea content is subsequently sifted, vetted, and ultimately solicited for adoption, community managers are expected to employ a sequence of persuasion activities that include either central cues that relate directly to idea attributes (e.g., value, affordability, and ease of use) or peripheral cues that do not directly relate to the ideas presented (e.g., feasibility, productivity, and performance). Therefore, to understand what drives idea adoption in VCCs, persuasion cues were first identified and their influence on idea adoption and the persuasion process was modeled; this, in turn, provided the theoretical basis for the conceptual model and hypotheses presented in this study.

3. RESEARCH MODEL AND HYPOTHESES

Drawing on previous theoretical arguments, this study developed a four-dimensional model to explain the likelihood of idea adoption in VCCs, as shown in Figure 1. In line with the ELM, the model proposed in this study consists of a peripheral route and a central route. The peripheral route to persuasion refers to the credibility of the idea source, which is intertwined with a set of peripheral cues that are not directly related to the specific content of the idea, including community recognition

of users, community recognition of ideas, and user engagement, while the central route consists of idea content quality, which is represented by idea length and supporting arguments. In addition, the community's absorptive capacity is closely related to the level of information participation of community reviewers, with higher absorptive capacity increasing their familiarity and motivation to process idea-related information. According to the cognitive load prevailing in the community, the number of ideas and the quality of idea content are the most important factors contributing to the cognitive load of the community, and the absorptive capacity of the community may have an impact on the relationship between the quality of idea content and idea adoption. Therefore, this study examines the moderating effect of community absorptive capacity on the relationship between idea content quality (represented by idea length and idea arguments) and idea adoption.

Figure 1. Research model



3.1 Peripheral Cues in VCCs

3.1.1 Community Recognition of Users

Community recognition and appreciation refers to the extent to which users are recognized and their contributions and participation in innovation activities are supported by both the community-hosting company and community peers (Qin & Liang, 2019). Although innovation communities are typically characterized by the voluntary engagement and contributions of community members, most community members prefer recognition for their contributions and friendly support from other

community members, community evaluators, and product owners (Qin & Liang, 2019). Typically, members in VCCs can freely join to view the community status of other members, their contribution level to the community, and the rewards they receive from the community. Thus, higher levels of recognition and appreciation can in part increase the influence of users and the positive role they play in the co-innovation and value creation process (Di Vincenzo et al., 2020; Jabr, Mookerjee, Tan, & Mookerjee, 2014).

In practice, community recognition and appreciation behavior can manifest in two forms: formal community recognition and informal peer recognition, both of which are likely to influence the adoption of ideas in VCCs (Lee et al., 2018). Formal community recognition reflects the level of support from community evaluators and the management company. This typically takes the form of bonus points, rewards, or recognition badges awarded by community management in the user's personal profile (Qin & Liang, 2019). Community management typically rewards users for their active contribution in answering and asking questions, writing posts, or sharing opinions in the community; therefore, the number of points a user receives may indicate, to some degree, the community's appreciation and interest in the user's contributions (Akar & Mardikyan, 2018; Akman et al., 2019). As VCCs accumulate a wealth of user-generated ideas, the evaluation of ideas and supporting elements consumes a large amount of intellectual resources and effort. In this situation, ideas contributed by highly recognized and valued users are more likely to attract attention and subsequently be adopted (Cheng et al., 2020). In light of these arguments, this study postulates that:

H1a: Formal community recognition, measured by the number of points awarded to a user, has a positive influence on idea adoption in VCCs.

Peer recognition refers to the informal recognition and support of a member by other members in the community. Informal peer recognition fosters an environment of appreciation that can increase innovation in the crowdsourcing community in several ways. Research has shown that user groups with a large number of friends and a diverse base of followers and social interactions have higher community influence and interconnectedness (Yazdanmehr, Wang, & Yang, 2020). Qin and Liang (2019) found that users with different numbers of friends have different influence on the likelihood of their ideas being adopted by the community. Similarly, Olmedilla et al. (2019) empirically studied online crowdsourcing activities and found that users' peer recognition and followership significantly influence the evaluation of other community members' ideas. Typically, all user contributions, such as ideas for product innovation or suggestions, can be evaluated by the community or other users for content quality and feasibility. Recognition and appreciation by other users enables verification of past interactions and thus offers community managers the opportunity to verify ownership of ideas, e.g., by linking directly to group archives. Furthermore, association with and membership in specific (sub)groups plays an important role in structuring reciprocal relationships. In particular, previous research suggests that online relationships actually increase status-based homophily (i.e., similarity in important attitudes, values, and beliefs), which in turn increases the chance of successful idea adoption (Groenewegen & Moser, 2014). In addition, friends and/or followers in the community can provide members with a better sense of belonging, trust, and satisfaction, which encourages users' contribution behavior in the community and, in turn, positively affects idea adoption (Qin & Liang, 2019). Therefore, this study postulates that:

H1b: Informal peer recognition, measured by the number of followers, has a positive influence on idea adoption in VCCs.

3.1.2 User Engagement

In VCCs, users' engagement reflects their ability and knowledge to identify product usage problems and propose possible innovative ideas and solutions that are consistent with what the operating company expects from the community in terms of feedback on its products and services (Akar & Mardikyan, 2018). Bovaird and Loeffler (2012) suggests that community users are expected to provide two types of intelligence in the innovation crowdsourcing process: first, the users' unmet needs in product or service use, and second, the solution that meets these potential needs. Chen, Magnusson, and Björk (2019) argue that the value of user contributions in crowdsourcing communities comes from the user's problem-solving ability. Typically, user engagement can be divided into two types: proactive engagement and reactive engagement (Qin & Liang, 2019). Proactive user engagement refers to the active and voluntary engagement and contributions of users (Mojtahedi & Oo, 2017), which is mainly manifested in the submission of ideas and suggestions by users to the community. In contrast, reactive user engagement refers to users' responses to information provided by other users (Changchit, Klaus, & Lonkani, 2020), which is mainly manifested in users' commenting and reviewing behavior on other users' ideas and suggestions in the community.

In practice, VCCs use various metrics and mechanisms to evaluate the effectiveness of proactive user engagement and contributions, such as the number of ideas posted by the user and adoption rate of previous ideas (Jabr et al., 2014; Qin & Liang, 2019). The ideas that users actively post tend to be associated with relatively new knowledge that is difficult to imitate and may have greater economic value. By continuously providing and sharing experiences in using products or services and suggesting valuable opinions and solutions to improve products or services, users benefit from critical thinking, improve their own innovation ability, and generate more valuable ideas (Loureiro & Kaufmann, 2018). Moreover, the more ideas users submit, the more feedback they receive; thus, interacting and sharing ideas with other community members promotes the diversification of user-related knowledge (Chen et al., 2019). In turn, the development of a diversified knowledge base, accompanied by accumulative learning dynamics, helps users gain a clearer understanding of products and the marketplace and assists them in improving their innovation capabilities (Luo et al., 2021; F. Wang et al., 2017). As users gain a clearer understanding of products and their relevant markets, ideas submitted by users are more likely to have operational and economic value; therefore, they are more likely to be supported and adopted by the community. Based on these arguments, this study postulates that:

H2a: The number of previous idea submissions by the user has a positive influence on idea adoption in VCCs.

In addition, idea adoption rate refers to the percentage of submitted user ideas that were adopted by the community-hosting company; this can provide insight into the effectiveness of user contribution behavior, user experience, and proactive engagement practices (Lipusch et al., 2020; Q. Liu et al., 2020). Users with high adoption rates may have better product knowledge (Dessart, Veloutsou, & Morgan-Thomas, 2015); consequently, their new ideas or practices are likely to have higher economic value, and their ideas are likely to receive greater appreciation and attention. In practice, when community reviewers are faced with a large number of ideas and cannot evaluate each idea in detail, the community tends to devote fewer knowledge resources in reviewing ideas submitted by users with high adoption rates; this could lead to a positive effect on the adoption of their ideas (M. Li et al., 2016). Therefore, this study posits that:

H2b: User idea adoption rate has a positive influence on idea adoption in VCCs.

On the other hand, users' reactive engagement and contribution through the practice of commenting and reviewing also facilitates knowledge integration in the idea crowdsourcing process.

Di Vincenzo et al. (2020) argue that ideas in crowdsourcing communities are more likely to survive when the crowd increases knowledge integrity through both sharing (generating ideas, supporting cases, or comments) and recognition (supporting others' comments and evaluating others' ideas). Also, the collaborative activity of users responding to other users' ideas in the community is a process of learning and sharing knowledge about products. However, if users allocate too many cognitive resources for commenting and evaluating other community users' ideas, the amount of available cognitive resources for submitting ideas will be reduced accordingly due to the limitation of cognitive resources. Previous research (Dessart et al., 2015; Heit & Rotello, 2012; Y. Hwang, 2016; Krufft et al., 2019) has shown that reactive engagement can reduce users' thinking ability and creativity compared to proactive engagement, making it less conducive for users to submit high-quality ideas. Thus, if a user devotes excessive cognitive resources to commenting and responding to other users' ideas and suggestions, they are less likely to improve their creativity, submit innovative ideas, and persuade the community to adopt their ideas. Accordingly, this study postulates that:

H2c: The number of comments posted by a user on other users' ideas has a negative influence on idea adoption in VCCs.

3.1.3 Community Recognition of Ideas

Community recognition of an idea reflects the extent to which that idea has gained the attention and appreciation of other community members, which can be measured by the number of supporters and points the idea has received (Di Vincenzo et al., 2020). Generally, as the crowdsourcing process grows in size and number of participants increases, employees must decide which ideas to focus their attention on. While activities around ideas definitely capture employees' attention, they also require significant allocation of time and resources to focus on a limited list of ideas (Bogers, Chesbrough, Heaton, & Teece, 2019). According to the resource-based view (Fahy, 2000), users comment and interact when they need resources from other users or they have resources that are needed by other users. The heterogeneous knowledge resources gathered during commenting activities advance users' understanding of the product and aid users in improving their creativity (Bayus, 2013). At the same time, the support or points given to the user's idea can clarify the extent to which the idea receives attention and recognition in the community. Previous studies have shown that how collaborators acknowledge certain ideas in the crowd is positively related to idea adoption in VCCs (Akar & Mardikyan, 2018; Haas et al., 2015). In particular, the number of idea supporters in VCCs may be perceived by community evaluators as an influential indicator of idea potential and creativity. Therefore, this study postulates that:

H3a: The number of idea supporters has a positive influence on idea adoption in VCCs.

In addition, the scores assigned to various aspects of innovation ideas in the form of crowdvotes or points represent the combined ratings of community users for that idea. Users in the community rate their support for the idea content according to their own interests, goals, or preferences, and then assign a score to the idea content (Di Gangi, Wasko, & Hooker, 2010). In a sense, the scores given to an idea reflect the degree to which community members support and value the user's idea (Yang & Han, 2019). Typically, ideas with high scores have high popularity in the community and in a sense represent the user's position in the community (Wu & Gong, 2019; Xiang, Du, Ma, & Fan, 2017). Yan et al. (2018) found that the more points and crowdvotes an idea receives, the more likely it is that a community evaluator will review and subsequently consider the idea for development. Similarly, Di Vincenzo et al. (2020) reported that highly popular ideas, i.e., ideas that have been voted for by a large number of members, are more likely to be endorsed by online collaborators, which in turn affects the likelihood of their selection and adoption. When community evaluators are cognitively

loaded, the score an idea receives is likely to be used as an indication of the idea's business value and potential. Compared to low-scoring ideas, community evaluators are likely to devote fewer cognitive resources to evaluating higher-scoring ideas, thereby promoting their adoption. Accordingly, this study postulates that:

H3b: The total number of scores awarded to an idea has a positive influence on idea adoption in VCCs.

3.2 Central Cues in VCCs

Typically, ideas submitted to VCCs vary widely in terms of content and detailed components. In particular, an idea with a low level of elaboration may contain few supporting elements and therefore receive a negative rating. As a result, managers may find this situation increasingly difficult to adequately understand and evaluate the idea and its associated content (Ma et al., 2019). Conversely, excessive elaboration of an idea may be perceived as too time-consuming and tedious to evaluate (Mack & Landau, 2020). Indeed, excessive elaboration may impose costs and cognitive load (intrinsic and extrinsic) on community managers as they process the idea (Qin & Liang, 2019). Previous research (M. Li et al., 2016; Q. Liu et al., 2020) has argued that community users are likely to have difficulty understanding the meaning and value of an idea if it is not properly articulated. While Haas et al. (2015) discussed this problem in the context of problem formulation, a similar argument can be extended to the level of idea formulation complexity. For example, lengthy idea formulations are less likely to be selected because they do not focus on key facets of an idea and are therefore excessively redundant or contain irrelevant elaborations. The clarity of an idea's content would then be reduced, negatively affecting its selection. Moreover, these ideas might be rejected due to their inherent complexity, leading community managers to use more sophisticated cognitive schemas to assimilate and digest them.

In the context of ELM, the idea content quality is an important cue that influences the cognitive load of community reviewers (Cheng et al., 2020; Krufft et al., 2019). It is closely related to the relevance and completeness of the idea, which in turn influence community perceptions of utility, satisfaction, and level of involvement in community co-innovation activities (Bi et al., 2017; Cyr et al., 2018; Hoornaert et al., 2017; Lee et al., 2018). The idea content quality can be assessed by the idea length and number of arguments associated with the idea. When users post an idea in the community, the idea length can influence the level of understanding of the ideas (Hossain & Islam, 2015b). Typically, users' ideas reflect their experiences or needs, which is relatively abstract and hinders the transfer of tacit knowledge. Thus, using short and abstract sentences to express ideas not only lacks enough details or omits some relevant information, but may also be difficult to understand because the expression is too abstract. Both situations affect the quality of idea content and have a negative impact on idea adoption (Haas et al., 2015). It has been argued that increasing the idea length can improve the clarity and comprehensibility of the idea and have a positive impact on idea adoption (Q. Liu et al., 2020). However, related research on innovation crowdsourcing has shown that ideas that are too long can reduce the quality of reasoning, which can affect the level of persuasion and engagement in promoting the idea (Lee et al., 2018). Similarly, information processing studies have highlighted that idea length is an indicator of idea complexity, which can negatively affect people's evaluations (Haas et al., 2015; Heit & Rotello, 2012). Given the limited cognitive resources of community reviewers, ideas that are too long impair community reviewers' understanding of ideas and thus negatively impact their adoption. As a result, it becomes more difficult for the reviewer to understand, evaluate, and assimilate the idea (C. Li et al., 2021). Collectively, these considerations suggest that ideas with an optimal level of elaboration are prioritized during the review and screening process because they have a more detailed and understandable presentation. Therefore, this study postulates that:

H4a: Idea length has an inverted U-shaped relationship with idea adoption in VCCs.

Similarly, supporting arguments can serve as a central cue that provides logical evidence and draws attention to the idea. When users post ideas to the community, they typically support them by including hyperlinks, images, and other arguments in their elaboration (Heit & Rotello, 2012). Depending on the perceived quality and strength of the arguments presented in the idea's content, users may be influenced to change their engagement in articulating and promoting the idea. This, in turn, can lead to a change in belief that the idea will be adopted (L. Li, Goh, & Jin, 2020). The credibility of an idea can also be improved by adding the source of the idea or by providing photographic evidence in the idea. In the context of VCCs, including supporting arguments to an idea can improve the idea's explanatory and persuasive capacity. Moreover, adding supporting arguments to an idea can attract the attention of other users in the community (Kruft et al., 2019; Ma et al., 2019). Thus, using arguments in ideas can improve the quality of ideas and promote their adoption by the community (Heit & Rotello, 2012). However, similar to idea length, an excessive amount of supporting arguments in an idea may obscure the core content of the idea and increase the cognitive load of the community evaluator, which may negatively affect the community evaluator's adoption of the idea. Therefore, the following hypothesis is proposed:

H4b: Idea arguments has an inverted U-shaped relationship with idea adoption in VCCs.

3.3 Moderating Role of Community Absorptive Capacity

In the context of VCCs, absorptive capacity refers to the community's ability to acquire, assimilate, and transform external knowledge sources and ideas into successful innovations (Apriliyanti & Alon, 2017; Cohen & Levinthal, 1990). As a knowledge-intensive activity, innovation ideas can be conceptualized as the result of collaboration with community members and the integration of new knowledge they share and co-create. However, the knowledge associated with innovation idea development tends to be largely tacit and can only be transferred to a certain extent (Medase & Barasa, 2019). As a result, communities with low absorptive capacity are limited in their ability to absorb and use new knowledge, making it difficult to identify ideas worth pursuing and adopting. To turn ideas into action, the most promising ideas, e.g. in terms of value creation and profitability, need to be identified using feasibility and business case analyses before they can be adopted. Since the primary purpose of innovation crowdsourcing is to generate ideas worth pursuing and adopting in an effective and efficient manner, VCCs need to develop appropriate structures and processes to successfully solicit ideas from the crowd of users. However, due to the dynamic nature of VCCs, the community's absorptive capacity is limited by the time and resource capacity of the individuals involved, even when capable structures are in place (Arias-Pérez, Lozada, & Henao-García, 2020). Therefore, the community's absorptive capacity is fundamental and significantly determines the success of the idea adoption process in VCCs.

In terms of ELM, the ability to assimilate external knowledge can influence the central route of persuasion in VCCs (Arias-Pérez et al., 2020). During the process of dissemination and transformation of ideas, new knowledge generated by participants and information related to the ideas are combined to establish a long-term relationship with others and build on pre-existing knowledge. Therefore, the ideas adopted by the community in a particular domain may indicate, to some extent, their familiarity with knowledge in that domain. As the community adopts more ideas on a particular topic, their knowledge in that area becomes more comprehensive and their receptivity becomes broader. However, in VCCs, individuals are typically guided by their interactions with other community members through their behaviors, cognitions, and social-exchange benefits (Luo et al., 2021). According to the social exchange theory (SET) (Cook, 2015), the absorptive capacity of a community also depends largely on the absorptive capacity of its individual members' cognitive structures (Apriliyanti & Alon, 2017). Cognitive structure guides an individual in identifying, selecting, and processing knowledge and thus determines behavior and decision making in the adoption of ideas (Abdul Basit & Medase, 2019;

Medase & Barasa, 2019). In this context, ideas that are too long can lead to cognitive load. If this is the case, reviewers in crowdsourcing communities are likely to perceive that complexity increases due to idea length, leading to a negative impact of idea length on adoption likelihood. However, if the absorptive capacity of the community is high, the sensitivity of community reviewers to the increase in idea length decreases, enabling them to reduce the cognitive load caused by the increase in idea length. When the community has a high level of receptivity, supportive arguments associated with the ideas can facilitate and promote the community's understanding of the ideas, which is more conducive to community adoption of ideas. In addition, improving the absorptive capacity of the community may also reduce the cognitive load of community reviewers due to the presence of excessive idea arguments. Based on these arguments, the following hypotheses are proposed:

H5a: Community absorptive capacity positively moderates the inverted U-shaped relationship between idea length and idea adoption, i.e., as community absorptive capacity increases, the positive slope of the inverted U-shaped relationship between idea length and idea adoption becomes steeper and the slope of the negative effect becomes flatter.

H5b: Community absorptive capacity positively moderates the inverted U-shaped relationship between the number of idea arguments and idea adoption, that is, as community absorptive capacity increases, the positive slope of the inverted U-shaped relationship between the number of idea arguments and idea adoption becomes steeper and the slope of the negative effect becomes flatter.

4. RESEARCH METHODOLOGY

To test the research model and hypotheses, this study used a widely accepted standardized analysis procedure, namely the hierarchical logistic regression model. Hierarchical regression analysis allows the relationship between a binary response variable and one or more independent variables to be predicted and measured in a stepwise fashion by estimating probabilities using a logistic function, which is the cumulative distribution function of the logistic distribution (Witte, Greenland, Haile, & Bird, 1994). As with any analytical endeavor, a significant portion of the research process was devoted to data collection, integration, and preprocessing. The preprocessed, analysis-ready data were then used to build several different predictive models (estimate results and test hypotheses). A set of standard measures was used to evaluate and compare the results of these models. In the final phase, two robustness tests were performed on the dataset to validate the estimation results.

4.1 Research Setting and Data Collection

The sample data used in this study was collected from the Tableau community (<https://community.tableau.com/s/ideas>); an online crowdsourcing platform created specifically to generate innovation ideas for Tableau business intelligence and analytics (BI&A) products and solutions. The Tableau product suite provides interactive visualizations and analytics through an intuitive interface for business users to create their own dashboards and analytics applications (Daradkeh, 2019a, 2019b). Tableau software aggregates data from many sources to create interactive, visual reports, dashboards and analytics that provide actionable insights to support data-driven decision making and deliver more customized products/services to their customers. Key analytic components of the Tableau product suite include: Tableau Desktop, Tableau Mobile, Tableau Public, Tableau Prep, Tableau Server, Tableau Online, Tableau Bridge, Tableau Data Management, Tableau Server Management and Tableau CRM (<https://www.tableau.com/products>).

The Tableau crowdsourcing community was selected based on its popularity and publicly available data related to the activities of members and hosting company in the online crowdsourcing platform. The Tableau community aims to connect the company with its users and customers to solicit suggestions for solving problems or generate ideas and inspiration for testing new projects. The Tableau community consists of BI&A users and customers from different countries, cultures,

backgrounds, and expertise in using various Tableau products. To participate, users can join the community for free by creating a profile with an email address. When they post an idea, they must provide a title and description and select a category to which the idea belongs. In addition to posting ideas, users can interact with other users by voting, awarding points, and commenting on others' ideas. The Tableau community does not offer monetary rewards for member participation or idea submission; instead, there are rewards in the form of recognition badges for users when their ideas are supported and subsequently adopted. Since Tableau.com provides BI&A software and most idea contributors in the community are users of BI&A products in their workplace, the Tableau community is considered a professional community of user innovators who share the same mindset and interest in gaining knowledge and insights about Tableau products through interactions focused on mutual support and idea sharing. As such, community members are more likely to engage in more professional interactions that allow them to accurately articulate and express their innovation ideas than users in non-professional or hybrid environments (M. Li et al., 2016; Q. Liu et al., 2020).

As part of the crowdsourcing process, the ideas and suggestions submitted by community members are forwarded directly to the respective product development team, based on the product line specified by the community member. The evaluation of the ideas posted on the crowdsourcing platform is performed incrementally. In sequence, each idea is evaluated by the individual moderators, then by the innovation group, and finally by the community managers. After the ideas have been evaluated, the community managers make decisions on whether to adopt the posted ideas in two phases. First, the evaluation team reads the ideas and identifies those that require action. These identified ideas are assigned a label to indicate their status. There are seven status categories, including "Open", "Archived", "Beta", "By Design", "Under Consideration", "Not Planned", and "Released". In addition to the status label, the review team provides a comment to the user to explain why the label was chosen. The comment may also include answers to questions posted with the idea. In this case, this comment is provided only once when the status label is assigned, and ideas received on the platform over time are separated from other comments with an explanation of the status label. In the second phase, the review team reviews the labeled ideas and adjusts the status labels based on progress. For example, an idea's "Open" label may be replaced with "Under Consideration" as the idea moves into the adoption process. When an idea is prioritized after review and a reasonable amount of support and positive voting scores from community members, the "Beta" label is assigned. Once adoption is complete, ideas are assigned "Released" status.

The Tableau crowdsourcing community received its first idea in July 2012, and to stabilize the interactions around all ideas, data was crawled for all ideas posted between July 2012 and December 2020. The data collection process was mainly divided into two rounds. The first round collects users' personal data, and the second round collects information on ideas and proposals submitted by users in all subsections and topics. Then, the user identifiers/username were used to integrate the two rounds of data. To ensure the quality of the data, this study applied the following three criteria to eliminate and sort out the data: (1) elimination of posts whose submission date was not within the time frame of the study; (2) elimination of posts with incomplete information; and (3) elimination of posts that were completely duplicated. Data were collected using a developed web crawling program, stored, and processed using Python language and statistical analysis.

To capture the essence of all data, all ideas were collected across all categories and topics. Currently, there are 47 idea categories in the Tableau business analytics community, including Reports, APIs and Embeddings, Dashboard, and Advanced Analytics, and users must select an idea category prior to submission. Descriptive information about the Tableau idea crowdsourcing community is shown in Table 1. During the data collection period, 9297 ideas were submitted, of which 768 ideas were considered for further development and converted into innovation outcomes. The idea adoption rate is 8.0%, which is consistent with other idea crowdsourcing platforms (Di Gangi et al., 2010; Q. Liu et al., 2020; Yang & Han, 2019). The majority of members, i.e. 8959 (or 80.6% of all members), posted only one idea on a single topic. Of the members who contributed more than one idea (i.e.,

serial contributors), 1633 individuals contributed 2331 ideas. In addition, 1296 of the 1633 members had not completed any ideas, while 154 individuals had completed 253 ideas. Because this study aims to understand the influence of persuasion cues on idea adoption in VCCs, idea classification and demographic characteristics of idea contributors were not considered.

Table 1. Tableau community profile (data sampled for the period between July 2012 and December 2020).

No. of members	11122	Total no. of ideas	9297	
No. of user groups	456	Adopted	768 (8%)	
		Topics	47	
Status*	No. (9297)	Points (2280436)	Supporters (81615)	Comments (61096)
Open	7657	1828500	38285	56461
Archived	872	436	112	315
Beta	6	30000	1418	231
By Design	9	45000	4150	145
Under consideration	50	25000	2500	531
Released	703	351500	35150	3414
Not planned	0	0	0	0
<i>Note:</i> Adopted ideas are those labeled Beta, By Design, Under Consideration, and Released, while non-adopted ideas are those labeled Open, Archived, Not Planned.				

4.2 Variables Selection and Measures

The variables in this study included one dependent (i.e., outcome/response) variable, seven independent (i.e., explanatory/predictor) variables, one moderating variable, and three control variables. The measurement of each variable is shown in Table 2. The dependent variable is idea adoption (Adopted), which is measured as a dichotomous variable, where 1 indicates that the idea was adopted, i.e., selected and turned into a formal organizational project for further development, and 0 indicates that the idea was rejected/not adopted by the community operators. The measurement of the dependent variable of idea adoption is mainly based on the status of the community idea. In the Tableau crowdsourcing platform, ideas posted by users are changed to different statuses after being reviewed by the community (the review time is usually one week). After in-depth discussions with Tableau community operators, it was confirmed that the four labels ‘Under Consideration’, ‘By Design’, ‘Beta’ and ‘Released’ indicate that the user’s ideas have been adopted and tuned into a formal project, and the value is 1. The other labels indicate that the ideas have not yet been adopted or are rejected by the community operators, and the value is 0.

The independent variables were divided into two types of persuasive cues, peripheral cues and central cues (see Figure 1). Peripheral cues include three dimensions: community recognition of users, community recognition of ideas, and user engagement. Community recognition of users is mainly subdivided into formal community recognition and informal peer recognition. Formal community recognition reflects the user’s appreciation and support by community operators, as measured by user points (i.e., the total number of points each user receives in the community). Informal peer recognition reflects the user’s appreciation and support by community peers, as measured by the number of followers (i.e., the total number of followers for each user in the community). Community recognition of ideas is primarily expressed by idea supporters (i.e., the number of users who supported/

Table 2. Description and definition of the study variables.

Type	Dimension	Variable Name	Variable Description
Dependent variable		Idea adoption (<i>Adopted</i>)	Idea labeled as Beta, By Design, Under Consideration, and Released means adopted and the value is 1, otherwise it is 0.
Independent variable	Community recognition of Idea	User points (<i>UPoints</i>)	Points awarded to the user, as displayed in his/her personal profile.
	Community recognition of Idea	Number of followers (<i>Followers</i>)	Number of followers a user has in the community.
	User engagement	Previously submitted ideas (<i>Submit</i>)	Number of ideas posted by user i before time t .
		Idea adoption rate (<i>Rate</i>)	Number of previously adopted ideas / Number of previously submitted ideas.
		Previously submitted comments (<i>Comments</i>)	Number of comments submitted by a user on other users' ideas.
	Community recognition of Idea	Idea supporters (<i>Supporters</i>)	Number of users who have supported / endorsed an idea
		Idea score (<i>Score</i>)	The number of points/votes an idea received from the community users.
	Idea content quality	Idea length (<i>Length</i>)	Number of words contained in the idea
		Idea arguments (<i>Arguments</i>)	Number of supporting arguments included in the idea content (packaged workbooks, Excel files, and/or multiple files/images).
Moderator		Community absorptive capacity (<i>CAC</i>)	Number of ideas adopted by the community in topic T_i by time t .
Control variable		Idea age (<i>IdeaAge</i>)	Total time of idea submission in the community.
		User's tenure in the community (<i>UserTenure</i>)	Number of months between the time user i posted his/her idea and the time he/she joined the community
		Community age (<i>CommunityAge</i>)	Number of months between the time user i posted his/her idea and the time the community was created.
Note: Variable abbreviation is in parentheses.			

endorsed an idea in a given time period) and idea scores (i.e., the total number of points/votes an idea received from community members). These two quantitative measures reflect the attention and support of the idea topic content by both the company and other online users in the community. User engagement was measured by three independent variables, namely previously submitted ideas, idea adoption rate, and previously submitted comments. The variable previously submitted ideas was measured by the total number of ideas submitted by each user in the community in a given time period. The variable idea adoption rate was measured by the average of adopted ideas for each user in the community. The variable previously submitted comments was measured by the total number of comments submitted by a user in response to other users' ideas in a given time period. This study focused on commenting rather than voting behavior because votes cannot be traced back to users,

while comments are associated with their respective usernames. The central cues were captured by the idea content quality, which was measured by idea length and idea arguments. The idea length variable was measured by the total number of words included in the idea posting. It should be noted that the Tableau crowdsourcing community does not specify a threshold for idea length. The idea arguments variable was measured by the number of supporting arguments (in the case of the Tableau community, these include packaged workbooks, Excel files, and/or multiple files/images) that the idea description disclosed.

Finally, this study controlled for idea age, user's tenure in the community, and community age to test whether any of these variables had a significant effect on idea adoption. Idea age was measured by calculating the time at which the idea was submitted to the community. User tenure in the community was measured in months by calculating the interval between the month of first community activity and the last month of data collection for this study. Community age was measured in months by calculating the interval between the month the community was established and the last month of data collection. By controlling for characteristics related to ideas, users, and community, model results can be estimated by reducing the number of confounding variables for estimating model results.

4.3 Models Development and Analysis

Given the dichotomous nature of the dependent variable (idea adoption), the Logit regression model was used in this study to explore the hypotheses. In predictive analytics, logistic regression models are a very popular probability-based classification algorithm that employs supervised learning (Sharda, Delen, & Turban, 2021). It has been used extensively in numerous disciplines, including information systems and innovation diffusion and adoption (Allison et al., 2017; M. Li et al., 2016; Q. Liu et al., 2020; Qin & Liang, 2019; Yan et al., 2018). Fundamentally, the Logit model is a binary selection model that assumes that the probability of occurrence of events obeys a logistic distribution. This study posited that the decision-making process of idea adoption in VCCs involves a sequence of persuasion activities and is determined by several peripheral and central cues. The peripheral cues consist of user points, number of followers in the community, previously submitted ideas, idea adoption rate, previously submitted comments, idea supporters, and idea score. The central cues include idea length and idea arguments. Also, the idea adoption process can be determined by control variables (idea age, user tenure, and community age) and an unobserved variance constant. Based on these arguments, the Logit model of idea adoption in the Tableau crowdsourcing community can be formulated as follows:

$$\begin{aligned} Pr(adopted_i = 1 | X_i) = & \Lambda(\alpha + \beta_1(IdeaAge) + \\ & \beta_2(UserTenure) + \beta_3(CommunityAge) + \beta_4(UPoints) + \\ & \beta_5(Follower) + \beta_6(Submit) + \beta_7(Rate) + \beta_8(Comments) + \beta_9(Supporters) + \beta_{10}(Score) + \beta_{11}(Length) + \beta_{12}(Arguments) + \\ & \beta_{13}(Length)^2 + \beta_{14}(Arguments)^2 + \beta_{15}(CAC) + \beta_{16}(Length * CAC) + \beta_{17}(Arguments * CAC) + \varepsilon_i) \end{aligned}$$

Where, $\Lambda(X) = e^x / (1 + e^x)$, α is a constant, and μ_i is an error term, i is the user and t is the time (month). β_j can be interpreted as the change made in the likelihood of idea adoption as each variable changes. More specifically, in the Logit model, β_j describes the magnitude of the contributions of the independent variables to the logarithm of the odds ratio, which is defined as the ratio of the probability that idea adoption will occur to the probability that idea adoption will not occur (i.e., $Pr(adopted_i = 1) / Pr(adopted_i = 0)$). Thus, an odds ratio greater than 1 indicates that the idea is more likely to be adopted in the community. The maximum likelihood estimation (MLE) method was used to estimate the coefficients of the independent variables. The multilevel logistic analysis xtlogit as implemented in Stata 14 was used to fit the model.

In this study, four Logit models were developed to test the research hypotheses hierarchically. The first three models were developed to test the effect of control variables, peripheral cues, and

Table 3. Descriptive statistics of variables (N = 9297)

Variable	Min	Max	Mean	Std. Dev.
Adopted	0	1	0.08	0.24
IdeaAge	1	92	54.02	17.92
UserTenure	1	92	66.37	15.87
CommunityAge	1	92	63.34	17.19
Upoints	0	88397	3586.86	831.39
Followers	0	82	31.26	5.10
Submit	16	142	54.73	9.84
Rate	0	0.12	0.33	0.08
Comments	0	15	0.02	0.08
Supporters	1	1530	205.14	9.88
Score	10	9580	322.12	11.83
Length	15	800	108.55	12.93
Arguments	0	4	1.28	0.64
CAC	15	142	88.26	13.64

central cues. Specifically, Model 1 was fitted to estimate the effect of control variables (i.e., idea age, user tenure, and community age) on idea adoption. In Model 2, the peripheral clues (i.e., user points, number of followers, previously submitted ideas, idea adoption rate, previously submitted comments, idea supporters, and idea score) were added to assess their effect on idea adoption, as hypothesized in H1a, H1b, H2a, H2b, H2c, H3a, and H3b, respectively. Model 3 included and tested the influence of idea content quality (i.e., idea length and idea arguments) on idea adoption, as hypothesized in H4a and H4b, respectively. The final model (Model 4) captures the interaction effects aimed at testing that community absorptive capacity positively moderates the inverted U-shaped relationships between idea length and idea arguments and idea adoption, as hypothesized in H5a and H5b, respectively.

5. RESULTS

5.1 Descriptive Statistics and Correlation Coefficient Testing

Table 3 reports the descriptive statistics for all variables used in the study. Considering that the data sample of the Tableau crowdsourcing community was from July 1, 2012 to December 31, 2020, the average number of user-generated ideas is 54.73 per month and the average number of visits is 30.59 per day. It is worth noting that online users, including users who posted and commented, have an average user score of 3586.86 and appear 0.33 times in the “Popularity List” column. The average idea score is 322.12, and the calculation method used in the Tableau community is as follows: answering or asking a question/posting an idea or commenting on an idea counts 10 points, marking an answer as the best answer counts 25 points, sharing another user’s idea counts 1 point, and sharing the user’s idea by other members counts 5 points. Since some of the independent variables have different ranges of values that are highly skewed, their logarithmic values are used in the Logit Regression analysis.

Table 4 shows the correlation coefficients for all variables used in the study. First, the correlations between all independent and control variables were examined and no evidence of multicollinearity was found. The highest correlations were between previously submitted ideas and user points (0.401, $p < 0.001$), idea adoption rate and number of followers in the community (0.487, $p < 0.001$),

Table 4. Correlation coefficients between variables

[illegible]

Table 5. Logit regression results with robust standard errors.

Independent Variables	(1) Control variables	(2) Direct effects	(3) Direct & quadratic effects	(4) Direct + quadratic + moderating effects
IdeaAge	-0.524*** (-20.24)	-0.481*** (-19.14)	-0.418*** (-17.64)	-0.312*** (-15.13)
UserTenure	0.153*** (14.84)	0.088*** (8.31)	0.079*** (8.71)	0.078*** (8.21)
CommunityAge	-0.211*** (-17.95)	-0.197*** (-14.53)	-0.194*** (-14.32)	-0.207*** (-20.94)
Upoints		0.072** (3.72)	0.072*** (3.76)	0.063*** (3.35)
Followers		0.025*** (1.75)	0.021*** (1.42)	0.032*** (2.32)
Submit		0.042*** (4.64)	0.041*** (4.58)	0.039*** (4.14)
Rate		0.022*** (1.51)	0.024*** (1.57)	0.015*** (1.32)
Comments		0.117 (13.89)	0.011 (13.56)	0.115 (13.15)
Supporters		0.021** (2.75)	0.020** (2.71)	0.031** (3.83)
Score		0.051*** (6.33)	0.050*** (6.14)	0.050*** (6.17)
Length		0.079*** (8.57)	0.221*** (9.67)	0.247** (6.67)
Arguments		0.028*** (3.22)	0.121*** (3.23)	0.082*** (2.37)
Length ²			-0.218*** (-6.12)	-0.112*** (-5.03)
Argument ²			-0.080** (-2.04)	-0.077* (-2.34)
CAC				0.143*** (6.23)
Length* CAC				0.035* (2.38)
Argument * CAC				0.012* (0.37)
Log-likelihood	-402.14	-391.83	-358.13	-347.26
Pseudo R^2	0.086	0.186	0.221	0.251
Constant	-4.6302*	-4.1482***	-3.8023***	-3.0737***
Note: Robust standard errors are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$				

and idea adoption rate and user points (0.406, $p < 0.001$). The variance inflation factors (VIFs) were also below the recommended threshold of 10 as suggested by Hair, Hult, Ringle, and Sarstedt (2017); overall, this indicates that the multicollinearity between the variables is not significant and is not expected to affect the results of the subsequent analysis.

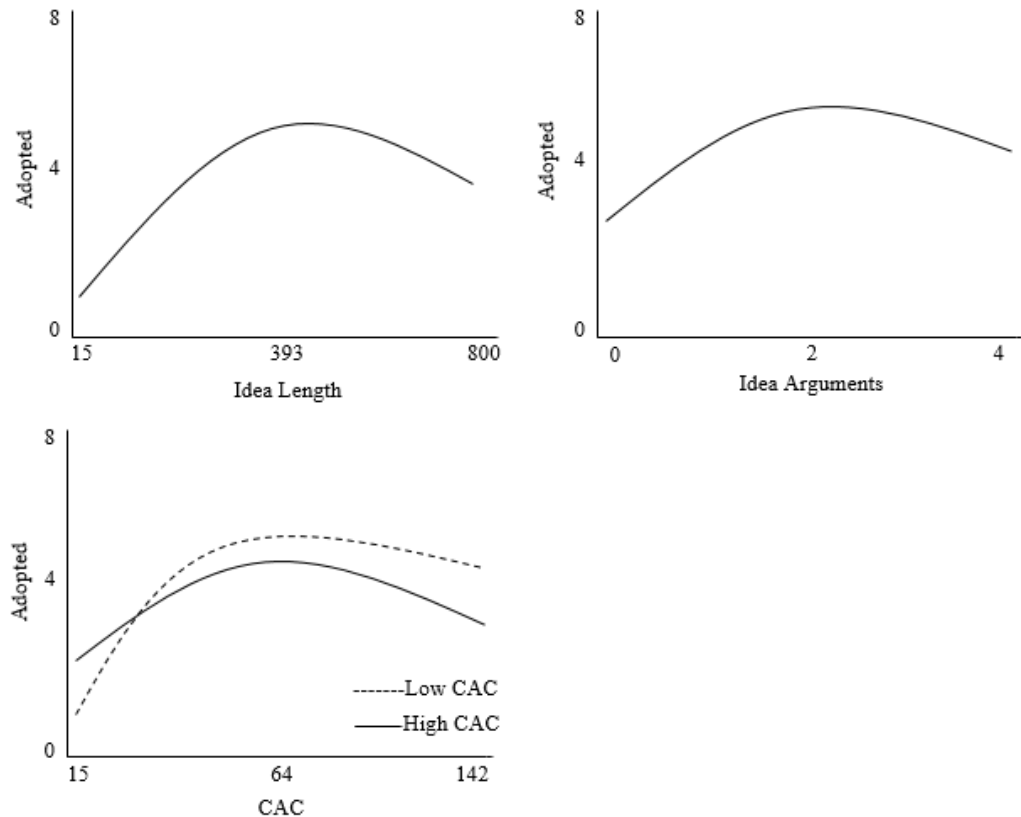
5.2 Hypotheses Testing

Table 5 reports the results of the Logit models. Column (1) shows the effect of the control variables on idea adoption; column (2) adds the effect of the main independent variables on idea adoption. Column (3) examines the quadratic effect estimates of idea length and number of idea arguments; column (4) examines the moderating effect of community absorptive capacity. The pseudo R-squared value

explaining the variance in idea adoption likelihood caused by the independent variables/predictors is 18.6% in column (2) with the main effects. This value increases to 22.1% and 25.1% in columns (3) and (4), respectively. When examining models (3) and (4) with the quadratic and moderating effects, it can be seen that all coefficients, except the coefficient of the variable comments, are statistically significant at the 1% level.

Returning to the detailed results as indicated in column (3) in Table 3, both user points ($\beta = 0.072$, $p < 0.001$) and number of followers ($\beta = 0.021$, $p < 0.001$) in the dimension of community recognition of users have a significant positive influence on idea adoption. Thus, H1a and H1b were supported; indicating that formal community recognition has a more positive influence on idea adoption than informal peer recognition. In the dimension of community recognition of ideas, both idea supporters ($\beta = 0.020$, $p < 0.05$) and idea score ($\beta = 0.050$, $p < 0.001$) were significantly positively associated with idea adoption, indicating that the higher the community recognition of the idea, the higher the likelihood of its adoption. Thus, H2a and H2b were supported. Regarding the dimension of user engagement, previously submitted ideas ($\beta = 0.042$, $p < 0.001$) and idea adoption rate ($\beta = 0.024$, $p < 0.001$) both have a significant and positive influence on idea adoption; indicating that proactive user engagement is positively related to idea adoption. However, reactive user engagement, measured by the number of comments posted by an idea generator on the ideas of other users in the community, did not significantly influence idea adoption ($\beta = 0.011$, $p > 0.001$). Therefore, hypotheses H3a and H3b were supported, whereas H3c was not supported.

Figure 2. Effect of idea length and idea arguments on idea adoption and moderating effect of community absorptive capacity (CAC)



In comparing column (3) with column (2), it is evident that the regression coefficients for idea length and idea arguments increase significantly after including their quadratic terms. This increase shows the importance of including the quadratic terms, since without them the estimates of these effects may be biased. As reported in column (3), the regression coefficients between the squared idea length, squared number of idea arguments, and idea adoption are ($\beta = -0.218, p < 0.001$) and ($\beta = -0.080, p < 0.05$), respectively. This indicates that there is an inverted U-shaped relationship between idea length, number of idea arguments, and idea adoption. Thus, H4a and H4b were supported. The results are shown in Figure 2 and Figure 3, respectively. From column (4), the interaction term between idea length and community absorptive capacity ($\beta = 0.035, p < 0.1$) was found to be significantly positively related to idea adoption, and community absorptive capacity can positively moderate the curvilinear relationship between idea length and idea adoption, indicating that H5a was supported, and the result is shown in Figure 4. In addition, based on the interaction term between the number of idea arguments and community absorptive capacity, the regression coefficient of idea adoption is significant ($\beta = 0.012, p < 0.1$). Thus, Hypothesis H5b was also supported, indicating that the number of arguments included in the idea may significantly influence community reviewers' understanding of the idea content during the idea evaluation process; consequently, community absorptive capacity may moderate the relationship between the number of idea arguments and idea adoption. Table 6 shows the results of the hypotheses tests.

Table 6. Hypotheses testing results

Dimension	Hypothesis	Remarks
Peripheral route (Affective)	H1a: Formal community recognition, measured by the number of points awarded to a user, has a positive influence on idea adoption in VCCs.	Supported
	H1b: Informal peer recognition, measured by the number of followers, has a positive influence on idea adoption in VCCs.	Supported
	H2a: The number of idea supporters has a positive influence on idea adoption in VCCs.	Supported
	H2b: The total number of scores awarded to an idea has a positive influence on idea adoption in VCCs.	Supported
	H3a: The number of previous idea submissions by the user has a positive influence on idea adoption in VCCs.	supported
	H3b: User idea adoption rate has a positive influence on idea adoption in VCCs.	Supported
	H3c: The number of comments posted by a user on other users' ideas has a negative influence on idea adoption in VCCs.	Not Supported
Central route (Cognitive)	H4a: Idea length has an inverted U-shaped relationship with idea adoption in VCCs.	Supported
	H4b: Idea arguments has an inverted U-shaped relationship with idea adoption in VCCs.	Supported
Moderator	H5a: Community absorptive capacity positively moderates the inverted U-shaped relationship between idea length and idea adoption.	Supported
	H5b: Community absorptive capacity positively moderates the inverted U-shaped relationship between the number of idea arguments and idea adoption.	Supported

Table 7. Robustness test results

Independent variable	(1) Exclude ideas submitted in the past 6 months	(2) Exclude ideas with length < 15
IdeaAge	-0.501*** (-15.26)	-0.382*** (-15.34)
UserTenure	0.076*** (5.12)	0.068*** (4.23)
CommunityAge	-0.250*** (-11.52)	-0.271*** (-14.30)
Upoints	0.038*** (2.41)	0.035*** (2.56)
Followers	0.024*** (3.36)	0.026*** (3.69)
Submit	0.043*** (4.45)	0.051*** (5.72)
Rate	0.032*** (2.18)	0.036*** (2.34)
Comments	0.251 (12.24)	0.219 (12.15)
Supporters	0.026*** (4.26)	0.021** (3.74)
Score	0.042*** (6.17)	0.049*** (6.51)
Length	0.261*** (4.66)	0.231** (4.52)
Arguments	0.081* (3.30)	0.089** (3.38)
Length ²	-0.236*** (-5.04)	-0.192*** (-4.31)
Argument ²	-0.093** (-1.62)	-0.095* (-1.42)
CAC	0.132*** (5.19)	0.161*** (6.23)
Length* CAC	0.045* (2.86)	0.043* (1.23)
Argument * CAC	0.031* (2.27)	0.017* (1.69)
Log-likelihood	-86.146	-85.720
Pseudo R^2	0.276	0.280
Constant	-3.677***	-3.101***
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$		

5.3 Robustness Testing

To validate the results, two robustness tests were performed on the dataset. First, since community reviewers need to spend a certain amount of time and effort to evaluate ideas, especially when many ideas are submitted in a given time period, the evaluation of ideas by community reviewers may be delayed by 7 days (the reason for choosing 7 days is that the fastest update cycle in the Tableau community is 1 week). This bias could cause a potential bias in the estimation. Therefore, the model was revalidated by eliminating idea submissions less than 7 days from data collection. In addition, when a user submits an idea, there may be errors in the submission. If the idea is submitted before editing is complete, such erroneous idea submission may bias the estimation results. Therefore, this study re-examines the model by eliminating idea content with an idea length of less than 15 words to further verify the positive relationship between idea length and idea adoption. Based on the results shown in Table 7, the results of the two verification tests of the new dataset agree well with the estimated results of the full dataset; this demonstrates the robustness of the results from this study.

6. DISCUSSION AND IMPLICATIONS

In today's dynamic and competitive business landscape, VCCs are quickly becoming a key differentiator for companies seeking to develop their innovation capabilities and strategic intelligence. While previous research has widely acknowledged the proliferation of VCCs as an important source for generating a wealth of creative ideas from the online crowd, there are few theoretical explanations of the persuasion mechanisms (routes) and cues that influence idea adoption in VCCs. This study contributes to filling this gap by developing a four-dimensional model of idea adoption in VCCs. More specifically, this study draws on the ELM and absorptive capacity to empirically analyze the influence of various persuasive cues on idea adoption in VCCs, using the Tableau idea crowdsourcing community as a case study.

First, the results of this study show that idea adoption in VCCs is influenced by several peripheral persuasion cues. In particular, community recognition of uses is positively related to the likelihood of idea adoption. However, compared to peer recognition, formal community recognition exerts a more significant positive influence on idea adoption. Community recognition of ideas in terms of number of supporters and score received for an idea has a positive influence on idea adoption. Proactive user engagement has a positive influence on idea adoption, while the relationship between reactive user engagement and idea adoption is not significant. This result suggests that reactive user engagement in the form of comments and received responses to other users' comments does not provide helpful and persuasive guidance that users need, and that scattered comments on other users' ideas do not contribute to the development of a knowledge base for improving, evaluating, and adopting ideas. Conversely, users who proactively engage in contributing ideas can improve their relevant knowledge base by learning from other users and receiving feedback on their shared ideas. By improving expertise or knowledge in a particular topic, it is easier for users to contribute high-quality ideas that are likely to be pursued and adopted (Qin & Liang, 2019; Yu & Liu, 2020).

Second, the central cue of idea content quality, represented by idea length and supporting arguments, is positively associated with idea adoption in the VCC. This result confirms the importance of idea content quality and highlights its influence on user attitude, engagement, and behavior in the context of VCCs. This is consistent with previous studies (Bi et al., 2017; Cheng et al., 2020; Di Vincenzo et al., 2020) suggesting that the adequacy and completeness of idea information is a precursor to users' perceptions of community usefulness, satisfaction, and engagement. However, the results of this study also show that idea length and number of idea arguments have an inverted U-shaped relationship with idea adoption, i.e., within a certain range, idea length and number of idea arguments have a positive influence on idea adoption, while outside this range, idea length and number of idea arguments have a negative influence on idea adoption. In the context of VCCs, the

articulation of ideas acquires a prominent feature due to the voluntary engagement of users, who tend to exhibit varying levels of time and effort devoted to the task of idea generation, and their willingness to articulate the idea in a structured online form (M. Li et al., 2016; Q. Liu et al., 2020; X. Liu et al., 2020). These results confirm that idea articulation and presentation have important implications for VCCs, as ideas with inferior presentation characteristics may be negatively evaluated by community managers in their review decisions.

Third, community absorptive capacity can positively influence the inverted U-shaped relationship between idea content quality and idea adoption, and accurate and quick understanding of the arguments supporting the ideas can improve the efficiency of idea adoption by community operators. That is, when idea length is short, community absorptive capacity can moderate the relationship between idea length and idea adoption. The absorptive capacity of the community promotes the positive influence of idea length on idea adoption and inhibits the negative influence of idea length on idea adoption when the idea length is long. This suggests that if the community with low absorptive capacity has the ability to access both direct and peripheral cues, it is likely to draw on multiple cues and that information seeking and subsequent engagement can be enhanced by design features and interconnectedness on the VCC (Luo et al., 2021; Medase & Barasa, 2019). In the case of the high absorptive capacity community, the browsing experience helps provide access to the arguments presented on the VCC. These findings provide valuable insights into the central and peripheral persuasion cues and mechanisms that influence idea adoption on VCCs, drawing several important implications for innovation crowdsourcing research and practice.

6.1 Theoretical Implications

The findings from this study make several contributions to the current literature. First, this study contributes to existing research on innovation crowdsourcing by providing an empirical analysis of the central and peripheral persuasion cues that influence idea adoption in VCCs. Because these communities are data-rich environments (Beretta, 2019), studies in this area have increasingly focused on examining what types of data may act as filtering heuristics to help managers select potentially attractive ideas (Yang & Han, 2019). This article extends these studies by including collaborator feedback and idea formulation as important determinants of idea identification and adoption. In this context, this study contributes to emerging calls for a better understanding of how new forms of online participation in idea generation (in this case, in terms of participants' ability to offer knowledge and feedback on others' ideas) may influence innovation adoption decisions.

Second, this study adds to the collaborative innovation literature by examining community members' engagement as contributors in the "elaboration phase" of the ideation process (Beretta, 2019). The findings suggest that different functional domains and expertise of members can be leveraged to complement ideas generated in VCCs to promote their adoption. Because innovation research tends to focus on either creative performance to generate novel ideas or innovative performance to implement ideas, the intermediate stages of the ideation process in which ideas are further articulated and subjected to evaluation are often marginalized (Loureiro & Kaufmann, 2018). For example, collaborative actions that involve knowledge sharing among members with different cognitive characteristics have been shown to stimulate the development of innovative ideas (E. Hwang, Singh, & Argote, 2019; C. Li et al., 2021). VCCs provide an open channel for collaborative ideas where customers can interact across different boundaries and contribute knowledge to others' ideas through their comments and opinions (Adameczyk et al., 2011). Therefore, this study seeks to complement current innovation research by examining the diversity of contributors and their influence on idea generation outcomes in the innovation context of a BI&A crowdsourcing community (Yang & Han, 2019).

Finally, this study extends current innovation management research by offering an alternative lens for managing innovation, and particularly innovation communities, as has traditionally been undertaken (Bogers et al., 2019). Specifically, research has suggested that companies should take an

open and collaborative approach to advance their business by engaging members in their innovation activities (Chesbrough, 2019; Najafi-Tavani et al., 2018). In support, empirical evidence shows the positive impact of member contribution to the business community (Bogers et al., 2017; Boon & Edler, 2018; von Hippel, DeMonaco, & de Jong, 2017), which includes the success of product innovation (Tsou & Chen, 2020). While it is widely recognized that the collaboration process itself can yield benefits for participants (Bogers et al., 2019), the current literature lacks an examination of the outcomes of participating in collaborative innovation from the members' perspective (Akman et al., 2019). Therefore, this study extends our understanding of the collectively created value that occurs as a result of an individual's participation in collaborative innovation.

6.2 Practical Implications

The results of this study have a number of important implications for innovation crowdsourcing practice. First, this study shows that the process of community adoption of ideas involves a number of persuasion activities, and while performing these activities, community reviewers are influenced by various peripheral and central cues in the adoption of user-generated ideas. Therefore, organizations can first screen out user groups that could potentially provide valuable ideas based on peripheral information such as the community status of idea contributors, past contribution behavior, and level of engagement. Then, the community status and recognition of idea contributors can be used as a guide for initial screening of ideas (Cheng et al., 2020). Then, ideas can be further filtered out from the screened user groups with high potential based on the peripheral cue of community recognition of ideas. Community recognition and appreciation is the result of peer evaluation, which can to some extent predict the market potential and needs of potential customers. Ideas with higher community recognition may be more successful after being turned into an innovative product. Therefore, companies can use the results of peer recognition and appreciation as additional evidence of an idea's value when analyzing ideas and conduct preliminary screening of ideas at the idea level based on the results of peer evaluations. Finally, companies can devote the core time and effort to conducting a detailed analysis and evaluation of screened-out ideas based on the central route and adopt the most valuable ideas in accordance with the company's operational and innovative capabilities and resources.

Second, the results of this study can be used as a reference for community reviewers to guide users to better formulate and describe their ideas. The study found that ideas with appropriate length and arguments are more likely to be adopted. Therefore, community reviewers can develop guidelines to help users better formulate their ideas and opinions before sharing them with their peers in the community. For example, users should be encouraged to add the necessary images or provide links to supporting documents when formulating their ideas. This practice is supported and confirmed by previous studies that have addressed the importance of ideas and feedback features on the likelihood of idea adoption. For example, based on the theory of message persuasion, Ma et al. (2019) argued that popular ideas are more likely to be adopted by companies and found that the length of ideas is positively related to the likelihood of adoption. Similarly, Shaikh and Levina (2019) applied message persuasion theory to show that the popularity of an idea and its innovation potential positively influence the likelihood of its adoption by the crowdsourcing company. Troise et al. (2020) studied prior participation behavior and idea adoption rate as characteristics of idea creators and their influence on idea adoption. Their study showed that users' previous participation behavior and the popularity of ideas positively influence the adoption and implementation of creative ideas, while the length of the description of ideas has no influence on the adoption of ideas.

Finally, the results of this study also have important implications related to the design of VCCs. For example, managers can focus on improving idea submission guidelines to ensure that the idea creator provides enough details about an idea to make it understandable while avoiding overly long and redundant descriptions. In addition, companies should consider offering rewards and incentives to motivate users not only to generate ideas, but also to participate in co-creating others' ideas when they engage in the co-innovation process (Akar & Mardikyan, 2018; Akman et al., 2019). Community

managers should recognize that community absorptive capacity is of great importance in reducing cognitive load in the idea adoption process. The results show that community absorptive capacity can positively influence the curvilinear relationships between idea length and idea adoption, and between idea arguments and idea adoption. To improve the community's own review capability, community reviewers should build experienced review teams for each topic area and provide specialized domain training to the review teams to broaden their knowledge of that topic area (Chen et al., 2019; Cheng et al., 2020). By acquiring specialized knowledge, community reviewers can improve their ability to understand users' ideas, which can reduce the cognitive load caused by the difficulty of understanding users' ideas to some extent and improve the efficiency of idea evaluation and adoption.

7. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

Notwithstanding the implications for research and practice discussed above, this study has a number of limitations that should be considered for future research. First, because the data collected for this study is based on a single VCC, namely the Tableau online idea crowdsourcing community, limitations may arise in terms of the extent to which these findings are generalizable, as differences between communities are not addressed in this study. The Tableau community is a professional community with a particular setting, considering its focus on promoting collaborative behavior among community members through the use of an interactive and collaborative ideation platform. Moreover, the results may not be generalizable to other VCCs that follow different review procedures. Nevertheless, there are a number of VCCs that focus on crowdsourcing ideas on business intelligence and analytics products, such as the Microsoft Power BI community (Yang & Han, 2019), which receives an abundance of ideas daily and uses a similar review mechanism. The findings and recommendations presented in this study could be applicable to other communities to the extent that they use similar review mechanisms as the community in this study.

Another limitation of this study lies in the persuasion processes and cues selected for investigation. Persuasion cues were derived from the literature according to their relevance in an innovation crowdsourcing context. Although the persuasion cues included in this study were confirmed as significant predictors of idea adoption in VCCs, other cues could be further explored, such as information-seeking cues and cerebral activities (e.g., positive thinking and sense-making). Future research could incorporate a broader set of online persuasion cues into the persuasion process as measured in various research settings. For example, independent members might engage in additional self-generated persuasion activities, such as active participation in decision making, interactions with collaborators, and information seeking. Comparing communities that focus on innovation with other types of VCCs would also be valuable.

Finally, this study only examined a web-based innovation crowdsourcing paradigm. It would be interesting to extend the research to an offline type of crowdsourcing. For example, individuals could be driven to participate in specific persuasion activities while volunteering. Similarly, support group members could receive benefits from engaging in persuasion activities. Applying the proposed model of this study in a different research setting would also provide an opportunity to make comparisons between different services and types of collaborations. It may be interesting for future research to examine whether similar outcomes related to idea adoption occur in other settings and other forms of online participation. For example, it would be informative to conduct a longitudinal study to examine how participation in persuasion activities changes member attitudes over the long term.

8. CONCLUSION

Drawing on the ELM and absorptive capacity, this study developed a conceptual model to explain the relationships between key persuasion cues and idea adoption in virtual crowdsourcing communities. The results of this study show that community recognition of users, community recognition of ideas,

and proactive user engagement are important persuasive cues that are positively related to the likelihood of idea adoption. Thus, this study provides theoretical evidence for the argument that idea adoption in VCCs is enabled by an interactive set of persuasion activities performed by community individuals and operators, with learning, absorption, and dissemination of knowledge playing important roles as mediators in the collaborative innovation process. Importantly, this study informs the management of collaborative innovation communities on how to facilitate and understand factors that drive community members to follow persuasion activities, and how to contribute to the co-creation and transformation of crowd-generated ideas into fruitful innovations by identifying ideas worth pursuing and adopting. This is particularly important in the context of collaborative innovation practice, where openness, interaction, ideation, co-creation of value, and sharing of resources with other contributors in the community are paramount to the creation and development of new ideas and product innovations.

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