The effects of online reviews on the popularity of user-generated design ideas within the Lego community

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Received 31 October 2021
Revised 8 March 2022
23 March 2022
6 April 2022
7 April 2022
Accepted 8 April 2022

Abstract

Purpose – This study aims to explore how online reviews and users' social network centrality interact to influence idea popularity in open innovation communities (OICs).

Design/methodology/approach – This study used Python to obtain data from the LEGO Innovation Community. In total, 285,849 reviews across 4,475 user designs between March 2019 and March 2021 were extracted to test this study's hypotheses.

Findings – The ordinary least square regression analysis results show that review volume, review valence, review variance and review length all positively influence idea popularity. In addition, users' in-degree centrality positively interacts with review valence, review variance and review length to influence idea popularity, while their out-degree centrality negatively interacts with such effects.

Research limitations/implications – Drawing on the interactive marketing perspective, this study employs a large sample from the LEGO community and examines user design and idea popularity from a community member's point of view. Moreover, this study is the first to confirm the role of online reviews and user network centrality in influencing idea popularity in OICs from a social network perspective. Furthermore, by integrating social network analysis and persuasion theories, this study confirms the interaction effects of review characteristics and users' social network centrality on idea popularity.

Practical implications – This study's results highlight that users should actively interact and share with reviewers their professional product design knowledge and/or the journey of their design to improve the volume of reviews on their user designs. Moreover, users could also draw more attention from other users by actively responding to heterogeneous reviews. In addition, users should be cautious with the number of people they follow and ensure that they improve their in-degree rather than out-degree centrality in their social networks.

The authors would like to thank the guest editor professor Chenglu Wang and anonymous referees for their constructive suggestions that have substantially improved this manuscript. Authors also grateful for Ms. Lan Xu from Northeastern University for her help during the data collection process. This project is funded by National Natural Science Foundation of China (grant number 72172030 and 71831005), China Scholarship Council (202006080012), the Fundamental Research Funds for the Central Universities (No. N2106009), and Trinity Arts and Social Sciences Benefaction Fund, Trinity College Dublin, Ireland.

European Journal of Marketing
Vol. 56 No. 10, 2022
pp. 2622-2648
Emerald Publishing Limited
0309-0566
DOI 10.1108/EJM-10-2021-0816

Originality/value – This study integrates social network analysis and persuasion theories to explore the effects of online reviews and users' centrality on idea popularity in OICs, a vital research issue that has been overlooked.

Keywords Online reviews, Open innovation, Network centrality, User design, Idea popularity

Paper type Research paper

Introduction

Organizations have continuously relied on their open innovation community (OIC) to collaborate with nonexpert customers for innovation purposes (Bayus, 2013). An OIC refers to a firm-hosted community platform that allows external users to exchange innovative ideas and share their own product designs to influence companies' new product design and development (Liu *et al.*, 2020) and thereby enhance innovation performance (Chesbrough, 2012). A report from the world's largest crowdsourcing platform (one form of OICs) – Eÿeka – suggests that 85% of the best 100 global brands have used crowdsourcing and deemed users (i.e. people contributing in OICs) one of their main vehicles to generate innovative product/service ideas (Yannig, 2015). Notable OIC examples include the LEGO community, Starbucks' MyStarbucksIdea community, Xiaomi's MIUI new product development community and Dell's IdeaStorm (Liu *et al.*, 2020). These firms incorporate valuable user-generated ideas into their new product development processes, generating innovative products that better cater for their customer preferences (Schlagwein and Andersen, 2014). Unsurprisingly, the notion of user design has received substantial attention from both academics and practitioners (Nishikawa *et al.*, 2013; Paharia and Swaminathan, 2019). Compared to other open innovation stakeholders (e.g. engineers or designers who do not work for companies), OIC users may have a better understanding of the brand and thus be more passionate about engaging in co-creation activities (Allen *et al.*, 2018; Fuchs and Schreier, 2011). For instance, studies have noted that almost three million UK consumers have voluntarily participated in co-innovation in the household product industry (von Hippel *et al.*, 2012).

Because of the large volume of user ideas submitted in OICs, user designs are implemented by companies at a very low rate. This has led to an increasing need to understand how to maximize the likelihood of user ideas being implemented by companies (Liu *et al.*, 2020). This understanding is important for both companies and OIC users. On the one hand, companies receive a large volume of ideas from their OIC users, thereby encountering great difficulties in evaluating and identifying promising users (Hofstetter *et al.*, 2018); while on the other, OIC users require quick responses from firms to improve their design ideas and increase the likelihood of their ideas being implemented by firms. Therefore, the efficient selection and screening of design ideas are critical for both OIC users and firms (Ma *et al.*, 2019). Accordingly, researchers have examined factors that determine the likelihood of idea implementation, among which idea popularity is a vital factor (Li *et al.*, 2016; Ma *et al.*, 2019; Schemmann *et al.*, 2016). Idea popularity denotes the total voting score of a user-generated idea in an OIC. Previous studies have argued that OIC users' voting for their preferred ideas creates a "wisdom of the crowds" effect and thus serves as a preselection process for idea implementation (Surowiecki, 2004). Such an effect implies that, although not every member in an OIC can provide valuable design ideas for companies, OIC members can collectively identify ideas that are valuable to companies (Schemmann *et al.*, 2016). As a result, companies have used OIC user voting to verify the popularity of a user design and predict its potential commercial attractiveness to target customers (Bartl *et al.*, 2012). Surprisingly, however, the existing literature has given little attention to factors influencing idea popularity in OICs, leading to an increasing call for research to understand how idea popularity is achieved in OICs (Schemmann *et al.*, 2016).

Admittedly, a handful of empirical studies have explored how the characteristics of ideas, such as the number of words in an idea, the idea's sentiment (O'Leary, 2016) and its language features (Noguti, 2016), can influence idea popularity. However, these studies have largely overlooked the fact that OICs are also social media platforms where companies encourage users to engage in interaction activities through commenting on and/or voting for user designs, which can generate a buzz and thus potentially influence the popularity of a user idea. For instance, when a user browses information relating to user designs in OICs, he/she is often exposed to high volumes of other reviewers' comments, which can significantly affect his/her product choice and decision-making processes (Cheung and Thadani, 2012). Thus, OIC users' perceptions, opinions and online behaviors can be influenced by other community members (Hofstetter *et al.*, 2018). Moreover, users' standing within their social networks can also determine their impact within OICs. The role of social network centrality dictates that users with higher centrality within their networks are more influential and persuasive than those with lower centrality (Valsesia *et al.*, 2020). For instance, users' prior participation in OICs can be an important signal of source credibility, which may have a substantial influence on community members' attitudes and behaviors (Li *et al.*, 2016). While previous studies have largely focused on how the key characteristics of a user design and a user can influence the perceptions and acceptance of his/her design, they have failed to consider collective influence by other users (Yang and Han, 2021; Zhu *et al.*, 2019). As a result, an attempt to understand user design and idea popularity from a community member's point of view is warranted (Akman *et al.*, 2019). Accordingly, our study aims to draw on persuasion theories and social network analysis to address two important questions:

RQ1. How do OIC reviews affect OIC members' preference for a user design?

RQ2. How does users' network centrality interact with such an effect?

The remainder of this study is structured as follows. We first present a review of the literature on user design in relation to OICs, review characteristics, network centrality and idea popularity to elucidate the research gaps in the existing literature. This is followed by our hypothesis development concerning the impact of review characteristics on idea popularity as well as the interaction effects between degree centrality and online reviews. We then introduce our methodology, followed by the detailed data analysis process, the hypothesis-testing results and presentation of the robustness of regression results. We conclude with a discussion of the results, the main theoretical and practical contributions and possible limitations and directions for future research.

Literature review and hypothesis development

User-design in open innovation communities and idea popularity

Open innovation, a process whereby companies collaborate with external stakeholders to gather innovative knowledge and resources for new product development, has become a pivotal approach to revitalizing a company's innovation processes (Chesbrough, 2003). Among various forms of open innovation practices, OICs have gained prevalence and changed how companies co-create with their customer base (Jensen *et al.*, 2014). Following service-dominant logic, companies no longer consider their users solely as buyers or consumers. Rather, users are treated as a prominent source for product co-creation and value co-creation (von Hippel, 2006). They are invited to contribute to online activities relating to product innovation, such as proposing new product ideas, sharing usage experience, commenting on user ideas and/or voting for their preferred products.

Studies have revealed that user engagement in OICs not only helps improve consumers' perception of a firm's innovation performance (Schreier *et al.*, 2012) but also enhances its new product performance (Allen *et al.*, 2018) and its product's actual market performance (Nishikawa *et al.*, 2017). Thus, prior research on OICs mainly focuses on the effectiveness of user design in regard to innovation outcomes as well as factors predicting idea implementation (Hoornaert *et al.*, 2017). Among the factors influencing the likelihood of idea implementation, idea popularity has been found to be a key determinant (Li *et al.*, 2016; Schemmann *et al.*, 2016) and has gained prevalence in the open innovation literature.

As virtual interactive marketing has been transformed from "word-of-mouth" toward "word-of-click" (Wang, 2021), users are not only empowered to post their own design ideas but are also involved in the peer evaluation of crowdsourced ideas that can potentially influence their popularity. This is a two-way communication that highlights users' responsiveness, interactivity and engagement (Nangpiire *et al.*, 2021; Wang, 2021). For instance, users can click "vote" or "like" buttons to indicate their preferences or leave a comment on a design idea. The adoption of online reviews and voting systems has motivated firms to look for more efficient ways to filter valuable ideas from a vast number of user-generated design ideas (Jensen *et al.*, 2014). Idea popularity is associated with users' interest in a design idea (Schemmann *et al.*, 2016) as well as its potential market acceptance (Ma *et al.*, 2019) and market success (Hofstetter *et al.*, 2018; Li *et al.*, 2016). Yang *et al.* (2022) also reveal that idea popularity and the number of reviews an idea receives have a direct impact on the likelihood of the idea being considered and implemented by a firm.

Despite the importance of idea popularity, the understanding of factors that influence idea popularity in the preselection phase is very limited. A handful of empirical studies have suggested that the characteristics of an idea such as its number of words and sentiment (O'Leary, 2016) and its language features (Noguti, 2016) are significantly correlated with idea popularity (i.e. its number of votes) (see Table 1). These studies have largely explored the phenomenon from the perspectives of the idea's creators and characteristics. Nevertheless, as firms increasingly rely on "wisdom of crowds" (Surowiecki, 2004) to identify valuable ideas for new product development (Hofstetter *et al.*, 2018; Schemmann *et al.*, 2016), OIC members' responses to crowdsourced ideas become increasingly important. However, OIC members' peer interaction and their interaction's impact on open innovation performance is under-explored (Yang and Han, 2021), with only limited research (O'Leary, 2016) linking review characteristics, such as review length and positive review sentiment, with idea popularity. This leads to an increasing call to understand user design and idea implementation from a community member's point of view (Akman *et al.*, 2019). Responding to this call, our study aims to draw on persuasion theories and social network analysis to explore how the characteristics of reviews a user design receives and the standing of a user within his/her OIC network influence idea popularity.

Review characteristics and idea popularity

Persuasion theories suggest that attitude changes occur when users are exposed to complex messages (O'Keefe, 1990) and have been widely used in the marketing and communication literature (O'Keefe, 1990; Verlegh *et al.*, 2015). Such messages can take the form of advertising messages (Fransen *et al.*, 2015), innovation ideas (Li *et al.*, 2016) and online review messages (Karimi and Wang, 2017). Online reviews, as a form of electronic word-of-mouth communication and user-generated content (Rasool and Pathania, 2021), serve as valuable messages that affect individuals' choices and decision-making processes (Cheung and Thadani, 2012; Zhang *et al.*, 2021). In various contexts, studies have investigated the impact of online reviews on consumption decisions, such as consumers'

Table 1.
Studies on antecedents and outcomes of idea popularity

Studies	Measurement for idea popularity	Antecedents or outcomes	Factors examined	Data source	Key findings
O'Leary (2016)	• Number of votes	Antecedents	• Number of comments • Number of words in comments and in the idea • Idea and comment sentiment	Canada's Digital Compass	The number of comments and the extent to which the sentiment in those comments is significantly related to the number of votes
Noguti (2016)	• Post score	Antecedents	• Post language (a number of language features)	Reddit	The number of adjectives and nouns, adverbs, pronouns, punctuation, question marks, advisory words and complexity indicators that appear in content community posts' titles are significantly related to post popularity
Hofstetter et al. (2018)	• No. of votes	Antecedents	• Social ties • Number of votes provided to others' ideas	Atizo.com	The no. of social ties solicited and the number of votes sent out significantly influence the number of votes received
Hwang *et al.* (2019)	• No. of votes	Antecedents	• Information networks	Crowdsourcing communities	Generalists' ability to create more popular ideas than nongeneralists is contingent upon the presence of deep knowledge
Schemmann *et al.* (2016)	• Positive or negative voting	Outcomes	• Idea implementation	Crowdsourcing platform	Idea popularity positively influence idea implementation

(*continued*)

Studies	Measurement for idea popularity	Antecedents or outcomes	Factors examined	Data source	Key findings
Li *et al.* (2016)	• The total voting score of an idea	Outcomes	• Idea implementation likelihood	Salesforce.com IdeaExchange and Dell IdeaStorm	Idea popularity positively influence the innovation idea's implementation likelihood
Ma *et al.* (2019)	• The ratio of the number of favorites to the number of page visitors in a user innovation	Outcomes	• Adoption status of user innovation	Online game user innovation community	Popularity of the innovation positively influence the adoption of a user innovation by the firm
Yang *et al.* (2022)	• No. of votes	Outcomes	• Idea consideration • Idea implementation	Microsoft PowerBI	Idea popularity positively influence the probability for the idea being considered and implemented

Table 1.

adoption intentions (Wu *et al.*, 2021), customer engagement (Mostafa, 2021) and purchase intentions (Tata *et al.*, 2020). Specifically, these studies have shown that review valence (Karimi and Wang, 2017; Kordrostami *et al.*, 2020; Yang *et al.*, 2012), volume (Kordrostami *et al.*, 2020; Yang *et al.*, 2012), length (Cao *et al.*, 2011; Karimi and Wang, 2017; Racherla and Friske, 2012) and variance (Karimi and Wang, 2017; Racherla and Friske, 2012) can potentially influence individuals' evaluation of products/services and their subsequent behaviors (e.g. product choice, purchase intention and loyalty). However, the impact of online reviews on user behaviors has received limited attention in an OIC context. Thus, we posit that user reviews in OICs serve as vital cues that can significantly influence other users' evaluation of a user idea. Given the limited empirical analysis of the effect of review characteristics on idea popularity, our study aims to complement the existing literature by exploring how review characteristics, namely, review volume, review valence, review variance and review length influence idea popularity in OICs.

Review volume is defined as the total number of reviews a user design receives in OICs. As a large pool of ideas and designs is submitted in OICs, community members are exposed to a massive amount of information and may experience difficulties in identifying and evaluating promising designs. This in turn can lead to low review capacity (Li *et al.*, 2016) and decreased efficiency in OIC members' decision-making process (Hong *et al.*, 2017). When individuals are uncertain about their preferences and judgements, the bandwagon effect – a desire to fit in the crowd – may occur (Leibenstein, 1950). In this case, individuals tend to unconsciously follow the majority in their decision-making processes. Given that review volume reflects aggregated judgement, a larger review volume can be a persuasive signal of the attractiveness of a design, which helps OIC members to make inference about the popularity of the design. As a result, they are more likely to like design ideas that have received a higher volume of reviews. This is also consistent with O'Leary's (2016) finding that the number of reviews is positively related to the popularity (i.e. the number of votes) of crowdsourcing ideas. Therefore, we assume that:

H1. Review volume has a positive effect on idea popularity in an OIC.

Review valence shows the general positive or negative nature of a review (Kordrostami *et al.*, 2020). For our purposes, we define review valence as the level of positivity in a review. Studies have revealed inconclusive findings regarding how review valence affects the way in which individuals perceive and respond to online reviews. On the one hand, some researchers have found that negative reviews have a greater effect on perceived usefulness (Purnawirawan *et al.*, 2012) and new product sales (Cui *et al.*, 2012) than positive reviews. This so-called "negativity bias" indicates that individuals tend to perceive negative reviews as having a higher credibility than positive ones in decision-making (Ballantine and Yeung, 2015). On the other hand, recent empirical research suggests that positive reviews have greater effects on attitude than negative reviews (Tata *et al.*, 2020). One widely accepted explanation for the impact of positive reviews is "confirmation bias," a psychological tendency whereby individuals tend to seek or interpret information in accordance with their prior beliefs and expectations (Nickerson, 1998) to affirm their decisions. In OICs, if a design idea receives more positive reviews, it conveys a message that this design is attractive to and favored by OIC members. In this case, positive reviews assist other users to develop a preference for a design idea. Consequently, users are more likely to like design ideas that have received positive reviews and thus increased idea popularity. Therefore, we assume that:

H2. Review valence has a positive effect on idea popularity in an OIC.

Review variance refers to the degree of dispersion of reviews of a user design (Langan *et al.*, 2017). Reviews with high levels of variance can reduce the diagnosticity of information, resulting in a greater perceived risk of adopting divergent opinions (Langan *et al.*, 2017; Wu *et al.*, 2021). Equivocal empirical evidence reveals both a positive and negative impact of review variance on product evaluation. For instance, prior research has uncovered that heterogeneous (high variance) reviews are more prone to generate biased evaluations than homogeneous (low variance) reviews because greater variance in conflicting reviews leads to greater perception of uncertainty (Park and Park, 2013) and loss of informativeness (Schoenmueller *et al.*, 2020). In contrast, high levels of review variance are believed to enhance the perceived uniqueness of products and thus lead to increased new product adoption (Wu *et al.*, 2021). As such, in the context of OICs, higher review variance indicates the self-expressiveness of a design idea (Rozenkrants *et al.*, 2017) and satisfies OIC members' thirst for design uniqueness (Wu *et al.*, 2021). In this case, high variance reviews serve as appealing and vivid information cues that attract OIC members' attention to and interest in a design idea (Kuan *et al.*, 2015) and thus increase idea popularity. Therefore, we assume that:

H3. Review variance has a positive effect on idea popularity in an OIC.

Review length denotes the word count in the text of a review (Lee and Choeh, 2014). In this study, we define review length as the average number of words in the reviews under the design. In the case of online product reviews, researchers have found a positive impact of review length on perceived review helpfulness (Hong *et al.*, 2017; Zhu *et al.*, 2020). In OICs, when community members browse reviews of a user design, their length reflects the informativeness of a review message (Lee and Choeh, 2014) and the effort of OIC members (Chen and Huang, 2013). Specifically, longer reviews are more likely to contain feedback or suggestions regarding user designs, which provides greater information value in helping OIC members to further understand the design ideas. Longer reviews also indicate that other users make greater effort to post reviews compared to those users who post shorter reviews (Chen and Huang, 2013). As a result, OIC members reading them are more likely to be inspired by the effort of other users and pay more attention to the design idea. Consequently, such design ideas become more popular among the OIC members and thus enhance idea popularity. Therefore, we assume that:

H4. Review length has a positive effect on idea popularity in an OIC.

Network centrality and idea popularity

Similarly to other online communities, OICs can be described as social media sites that allow users to communicate and exchange their opinions through commenting on and voting for user ideas. In the realm of social network analysis, social networks are formed by nodes and ties that connect different nodes (Wellman, 1983), according to which analysis OICs are informal social networks where each user is a node and users are connected by social ties through social interactions. Moreover, social network analysis posits that a node's structural position in the social network determines its outcomes (Borgatti and Ofem, 2010). As such, users' standing within their social networks can determine their impact in OICs. Such an impact can be captured by the concept of network centrality, which refers to the importance of a node's location in a social network (Grewal *et al.*, 2006; Muller and Peres, 2019). Network centrality thereby reflects a user's importance or influence in a social network (Valsesia *et al.*, 2020). Users with higher degree centrality (i.e. social hubs) can be expected to be more influential and persuasive users who build more social connections with many others (Valsesia *et al.*, 2020).

However, to the best knowledge of the authors, no empirical studies have examined how users' network centrality influences their idea popularity, resulting in a research gap.

Because a user's degree centrality describes the number of social ties a user possesses relative to other users in his/her social network (Muller and Peres, 2019), users with higher degree centrality in OICs are those who build more links with others in a given social network (Akdevelioglu and Kara, 2020). Previous research has indicated that idea popularity in a social network can be influenced by social navigation through social ties (Canali *et al.*, 2010) as well as the number of social ties a user solicits (Hofstetter *et al.*, 2018). Therefore, users with higher degree centrality can take advantage of their extensive ties to spread design ideas (Muller and Peres, 2019) and thus become more influential in affecting idea popularity. Given that the social links among users are directional (Canali *et al.*, 2010), two types of degree centrality, in-degree centrality (the number of followers) and out-degree centrality (the number of followings) (Valsesia *et al.*, 2020), can represent the social influence of a user. As in-degree centrality (or inbound links) and out-degree centrality (or outbound links) represent two different directions of user social ties, we assume that they have opposing effects on the relationships between review characteristics and idea popularity.

Social network analysis argues that users with higher in-degree centrality build more inbound links with others, compared to those with lower in-degree centrality (Canali *et al.*, 2010). Hence, they have a wider user base and thus are more likely to influence other community members (Carter *et al.*, 2007). In OICs, a user with a larger number of followers means that a substantial number of community members is willing to respond to what the user submits (Valsesia *et al.*, 2020). Moreover, if a user has more followers, more members can receive notifications when he/she creates a new submission. In this case, a user with more followers is more influential and has greater power in shaping members' attitudes than those with fewer followers (Dinh and Lee, 2021), which makes his/her designs more visible than others, and thus more OIC members are influenced by reviews. As a result, the impact of online reviews on idea popularity is more salient when a user has higher in-degree centrality.

In contrast to in-degree centrality, users with higher out-degree centrality builds more outbound links with others (Canali *et al.*, 2010). The number of OIC users that a user follows is deemed an indicator of the extent of their out-degree centrality (Valsesia *et al.*, 2020). A user following fewer others in OICs can also be perceived as more autonomous and influential in his/her social networks, which makes him/her less susceptible to influence from others (Aral and Walker, 2012). In contrast, if a user follows a relatively large number of others, he/she is more prone to be affected by outside opinions (Aral and Walker, 2012) and thus his/her influence and autonomy in an OIC (Valsesia *et al.*, 2020) may decrease. In this case, because his/her designs are both less visible than others and less likely to receive attention from OIC members, OIC members are less likely to be influenced by such reviews. As a result, the impact of online reviews on idea popularity is less salient when a user has higher out-degree centrality. Accordingly, we assume that in-degree centrality and review characteristics positively interact to influence idea popularity, whereas out-degree centrality and review characteristics negatively interact to influence idea popularity:

H5. In-degree centrality positively interacts with (*a*) review volume, (*b*) review valence, (*c*) review variance and (*d*) review length to influence idea popularity in an OIC.

H6. Out-degree centrality negatively interacts with (*a*) review volume, (*b*) review valence, (*c*) review variance and (*d*) review length to influence idea popularity in an OIC.

Research methodology

Data collection

The data were collected from the LEGO Innovation Community (https://ideas.lego.com), which was officially launched in April 2014. The LEGO Innovation Community is an online user community that collects user-generated designs and has been widely applied in the open innovation and user design literature (Jensen *et al.*, 2014; Schlagwein and Andersen, 2014). In this community, users can freely register accounts, publish their own designs, follow other users, post comments and show support for other users' designs. There are three main sections – activities, contests and product ideas sections – in the LEGO Innovation Community. In the activities section, users can participate in challenges assigned by the OIC, while in the contests section they can actively engage in themed contests released irregularly by the OIC. Users win prizes for submitting creative ideas, such as LEGO sets, rare items or free trips. In the product ideas section, the community encourages users to become real designers and submit their product ideas. Idea implementation requires a long-term process, as it may take up to several years to adopt and innovate a design idea. Specifically, before getting ideas evaluated by experts, users need to receive at least 100 likes in the first 12 months, 1,000 likes in the subsequent six months and over 5,000 likes in the final six months. Only ideas that receive over 10,000 likes will be evaluated by experts from the LEGO company. The potential ideas will be selected by LEGO and introduced to the market as part of the LEGO IDEA product series.

In this study, we focused only on user designs submitted to the product ideas section (ideas.lego.com/projects/create). We used Python to collect all the design ideas submitted between March 31, 2019, and March 31, 2021. All the information regarding the respective users, their design presentations and the reviews for each design were collected during the same period. Data were then integrated and matched based on the design's identification. After the deletion of duplicated designs, the data contained 285,849 reviews across 4,475 user designs.

Data management

We considered each product design as one individual case in the data management process. Each case includes three categories of information, namely, design presentation, reviews/likes received and user information (see Table 2). The design presentation contained such information as when the user uploaded the design, the number of updates during this period and the pictures and descriptions of the design. Each review contained evaluation of the design from other users. The user information involved the number of followers and followings.

Measures

The measures used in our study were all extracted from the LEGO Innovation Community (see Table 2). Our independent variables comprised characteristics of online reviews, namely, review volume, review valence, review variance and review length. We used the total number of reviews (excluding the number of user responses) to measure review volume. Review valence was measured by its positivity, whereas review variance was measured by the differences in extremity and emotionality (Rocklage *et al.*, 2018). Review length was measured by the mean score of the lengths of all reviews each design received. To measure review variance and valence, we used an Evaluation Lexicon to conduct computational linguistic analysis (Rocklage and Fazio, 2020; Rocklage *et al.*, 2018), which is a program used for automated text analysis that has been proved to have good validity in both natural and well-controlled lab conditions (Rocklage and Fazio, 2020). Our moderators included the in-degree centrality and out-degree centrality, which reflects the user's social network centrality. Following Valsesia *et al.* (2020), in-degree centrality was measured by the number of followers, whereas out-degree centrality was

Table 2. Variables and measurements

Types	Variables	Measurements
Control variables	No. of designs	No. of submitted designs
	Experience	Years that a user registered as a community member
	Time	The time distance between submission date to March 21, 2021, of the design
	No. of pictures	No. of pictures included in the presentation of the design
	Length of description	No. of words used to describe the design
	No. of updates	No. of updates on the design
Independent variables	Review volume	Total No. of reviews excluding the No. of designer's responses
	Review valence	The valence of a review refers to the level of positivity in a review
	Review variance	The degree of dispersion of reviews (the deviation from the midpoint of the valence scale)
	Review length	The average No. of words in the reviews under the design
Moderator	In-degree centrality	No. of followers
	Out-degree centrality	No. of followings
Dependent variable	Idea popularity	No. of likes that a design receives

measured by the number of followings. We used the number of voting "likes" to measure our dependent variable, namely, idea popularity. We also controlled variables related to the number of designs, user experience and design presentation, such as time, the number of pictures, length of description and number of updates.

Results

Data analysis method

We used the ordinary least squares estimation method to test our hypotheses. We used a STATA 16 command, "reg," for the analyses. A White Test was carried out by STATA to test heteroscedasticity. The White Test returned good results ($Prob>chi^2 = 0.000$), suggesting that there is no heteroscedasticity concern in our study. The regression model is as follows:

$$\begin{aligned} Idea\ Popularity = {} & \beta_1 No.\ of\ Designs + \beta_2 Experience + \beta_3 Time + \beta_4 No.\ Of\ pictures \\ & + \beta_5 Length\ of\ Description + \beta_6 No.\ of\ Updates + \beta_7 Review\ Volume \\ & + \beta_8 Review\ Valence + \beta_9 Review\ Variance + \beta_{10} Review\ Length \\ & + \beta_{11} In - degree\ Centrality + \beta_{12} Out - degree\ Centrality \\ & + \beta_{13} In - degree\ Centrality * Review\ Volume \\ & + \beta_{14} In - degree\ Centrality * Review\ Valence \\ & + \beta_{15} In - degree\ Centrality * Review\ Variance \\ & + \beta_{16} In - degree\ Centrality * Review\ Length \\ & + \beta_{17} Out - degree\ Centrality * Review\ Volume \\ & + \beta_{18} Out - degree\ Centrality * Review\ Valence \\ & + \beta_{19} Out - degree\ Centrality * Review\ Variance \\ & + \beta_{20} Out - degree\ Centrality * Review\ Length \end{aligned} \tag{1}$$

Table 3 summarizes the descriptive statistics of key variables included in this study as well as their correlation coefficients and variance inflation factor (VIF) values. The correlation between review variance and valence was −0.798, indicating a high correlation. Therefore, we tested if this high correlation poses concerns for multicollinearity issues. Our key statistics (see Tables 3 and 4), with VIF ranging between 1.003 and 2.893, heterotrait-monotrait ratio of correlations (HTMT) scores lower than 0.798, eigenvalue between 0.191 and 1.772 and condition indices between 1.143 and 3.477 are all within the recommended thresholds, suggesting no multicollinearity concerns (Kleinbaum *et al.*, 2013). Moreover, the valence of reviews indicates the favorability of a design, whereas the variance of reviews reveals the inconsistency among reviews (Wang *et al.*, 2015). Thus, we believe that these two variables are distinct. Following other studies (Langan *et al.*, 2017; Srivastava and Kalro, 2019; Zhu *et al.*, 2020), we include both review valence and review variance in the final analysis.

Regression results

The hypothesis-testing results with standardized coefficients are reported in Table 5. Model 1 accounts only for the impact of control variables on idea popularity. Model 2 reports the impact of four independent variables on idea popularity. Model 3 tests the moderating effect of users' degree centrality. As shown in Model 1, all control variables are found to influence idea popularity.

H1 to *H4* proposed that review volume, valence, variance and length had positive effects on idea popularity. As hypothesized, our results show that review volume ($\beta = 0.528$, $p < 0.01$), review valence ($\beta = 0.133$, $p < 0.01$), review variance ($\beta = 0.095$, $p < 0.01$) and review length ($\beta = 0.190$, $p < 0.01$) positively influence idea popularity. Therefore, *H1*, *H2*, *H3* and *H4* are supported.

H5 predicted that in-degree centrality positively interacts with review characteristics to influence idea popularity. The regression results (Model 3) show that in-degree centrality negatively interacts with review volume ($\beta = -0.041$, $p < 0.01$) to influence idea popularity. Thus, *H5a* is not supported. However, in-degree centrality positively interacts with review valence [$\beta = 0.349$, $p < 0.01$; Figure 1(a)], review variance [$\beta = 0.221$, $p < 0.01$; Figure 2(a)] and review length [$\beta = 0.069$, $p < 0.05$; Figure 3(a)] to influence idea popularity. Thus, *H5b*, *H5c* and *H5d* are supported. As shown in Figures 1 (a), 2(a) and 3(a), when in-degree centrality is low, the impacts of review valence and variance on idea popularity is negative, while the impact of review length on idea popularity is positive. When in-degree centrality increases, the impacts of review valence and variance on idea popularity become positive, while the positive impact of review length on idea popularity becomes more salient.

H6 predicted that out-degree centrality negatively interacts with review characteristics to influence idea popularity. The regression results (Model 3) show that out-degree centrality does not interact with review volume ($\beta = 0.005$, $p = 0.235$) to influence idea popularity, but negatively interacts with review valence [$\beta = -0.261$, $p < 0.05$; Figure 1(b)], review variance [$\beta = -0.156$, $p < 0.01$; Figure 2(b)] and review length [$\beta = -0.046$, $p < 0.05$; Figure 3(b)] to influence idea popularity. Thus, *H6b*, *H6c* and *H6d* are supported, but *H6a* is not. As shown in Figures 1(b), 2(b) and 3(b), when out-degree centrality is low, the impacts of review valence, variance and length on idea popularity is positive. When out-degree centrality increases, the impacts of review valence and variance on idea popularity become negative, while the positive impact of review length on idea popularity becomes less salient.

Table 3.
Correlation matrix

Variables	Mean	SD.	VIF	1	2	3	4	5	6	7	8	9	10	11	12	13
1. No. of designs	13.250	20.880	1.210	1												
2. Experience	2.277	142.900	1.177	*−0.099*	1											
3.Time	202.702	142.600	1.003	0.021	−0.007	1										
4. No. of pictures	8.348	4.066	1.188	*−0.049*	*−0.148*	*0.025*	1									
5. Length of description	202.100	149.300	1.193	*0.075*	*−0.056*	−0.012	*0.323*	1								
6. No. of update	0.733	1.916	1.206	*0.035*	*−0.165*	−0.012	*0.145*	*0.190*	1							
7. Review volume	46.050	78.230	1.313	*0.072*	*−0.188*	0.011	*0.167*	*0.128*	*0.365*	1						
8. Review valence	7.619	0.242	2.867	0.008	*−0.052*	0.022	*0.056*	−0.0004	*−0.050*	*−0.075*	1					
9. Review variance	0.636	0.948	2.893	−0.002	*−0.070*	*−0.030*	−0.010	*0.033*	*0.071*	*0.109*	*−0.798*	1				
10. Review length	8.689	3.112	1.274	*0.062*	*−0.297*	0.011	*0.205*	*0.246*	*0.201*	*0.242*	*−0.148*	*0.211*	1			
11. In-degree centrality	154.900	295.200	1.362	*0.386*	*−0.145*	*0.027*	*0.112*	*0.094*	*0.099*	*0.291*	0.0001	*0.035*	*0.176*	1		
12. Out-degree centrality	497.200	6,677	1.072	0.011	*−0.027*	0.003	*0.026*	−0.010	0.011	*0.152*	*−0.027*	0.017	−0.004	*0.215*	1	
13. Idea popularity	610.000	1,122.000	–	*0.059*	*−0.291*	0.020	*0.205*	*0.148*	*0.330*	*0.629*	−0.006	*0.098*	*0.372*	*0.388*	*0.037*	1

Note: Correlation provided in italics is significant at the 0.1 level

Table 4. HTMT, eigenvalue and condition index

Variables	Eigenvalue	Condition index	1	2	3	4	5	6	7	8	9	10	11	12	13
1. No. of designs	1.772	1.143													
2. Experience	1.336	1.316	0.099												
3.Time	1.058	1.479	0.021	0.007											
4. No. of pictures	1.003	1.519	0.049	0.148	0.025										
5. Length of description	1.000	1.521	0.075	0.056	0.012	0.323									
6. No. of update	0.998	1.523	0.035	0.165	0.011	0.145	0.190								
7. Review volume	0.917	1.589	0.072	0.188	0.011	0.167	0.128	0.365							
8. Review valence	0.694	1.827	0.007	0.052	0.022	0.056	0.000	0.049	0.075						
9. Review variance	0.661	1.872	0.002	0.070	0.030	0.010	0.033	0.071	0.109	0.798					
10. Review length	0.558	2.036	0.062	0.297	0.011	0.205	0.246	0.201	0.242	0.148	0.211				
11. In-degree centrality	0.498	2.157	0.386	0.145	0.027	0.112	0.094	0.099	0.291	0.000	0.035	0.176			
12. Out-degree centrality	0.191	3.477	0.011	0.027	0.003	0.026	0.010	0.011	0.152	0.027	0.016	0.004	0.215		
13. Idea popularity			0.059	0.291	0.020	0.205	0.148	0.330	0.629	0.006	0.098	0.372	0.388	0.036	

Table 5. Hypothesis testing results

Variables	Model 1	Model 2	Model 3
Control variables			
No. of designs	0.030** (0.014)	−0.002 (0.011)	−0.071*** (0.011)
Experience	−0.223*** (0.014)	−0.102*** (0.012)	−0.093*** (0.011)
Time	0.019 (0.014)	0.012(0.011)	0.008(0.010)
No. of pictures	0.120*** (0.015)	0.046*** (0.012)	0.030*** (0.011)
Length of description	0.043*** (0.014)	−0.005 (0.012)	−0.003(0.011)
No. of update	0.266*** (0.014)	0.076*** (0.012)	0.071*** (0.011)
Independent variables			
Review volume		0.528*** (0.012)	0.560*** (0.015)
Review valence		0.133*** (0.018)	0.167*** (0.018)
Review variance		0.095*** (0.018)	0.118*** (0.018)
Review length		0.190*** (0.012)	0.163*** (0.011)
Moderators			
In-degree centrality			0.144*** (0.018)
Out-degree centrality			−0.172** (0.027)
Volume * In-degree centrality			−0.041*** (0.008)
Valence* In-degree centrality			0.349*** (0.029)
Variance* In-degree centrality			0.221*** (0.030)
Length* In-degree centrality			0.069*** (0.012)
Volume * ut-degree centrality			0.005(0.004)
Valence* Out-degree centrality			−0.261** (0.048)
Variance* Out-degree centrality			−0.156*** (0.043)
Length* Out-degree centrality			−0.046** (0.019)
Cons	2.49e-08	1.50e-08	−0.013
Adjusted R^2	0.185	0.474	0.545
AIC	11791.710	9834.524	9195.390
BIC	11836.560	9904.993	9329.921

Notes: ***p < 0.01; **p < 0.05; and *p < 0.1. Standard errors in parentheses. AIC = Akaike information criterion; BIC = Bayesian information criterion

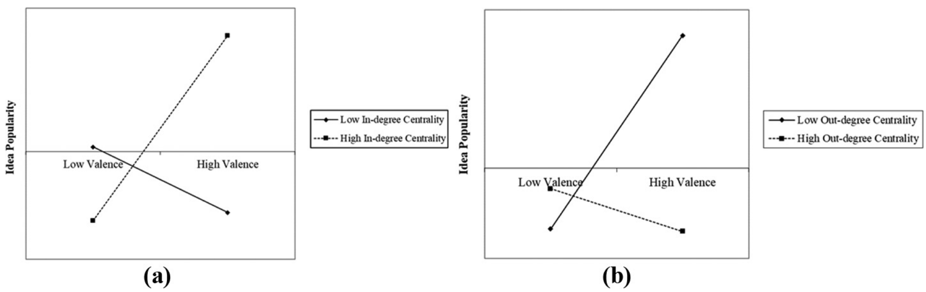


Figure 1. Interaction between degree centrality and review valence

Notes: (a) Valence* in-degree centrality; (b) valence* out-degree centrality

Robustness

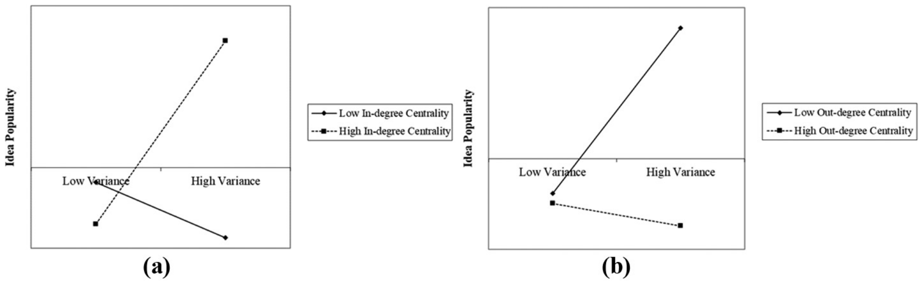
We used three different methods to test the robustness of our results. First, we transformed our data using winsorization (Lucas and Crosier, 1982) and tested our hypotheses with the winsorized data set. The regression results show that the model has an acceptable model fit (adjusted $R^2_{\text{Model 1}} = 0.195$; adjusted $R^2_{\text{Model 2}} = 0.610$; adjusted $R^2_{\text{Model 3}} = 0.664$) and the coefficients of the main explanatory variables remain consistent and significant (see Appendix 1).

Second, we tested the robustness using the generalized method of moments (Andersen, 2008). Specifically, we introduced control variables into the model and then added explanatory variables and moderating variables in Models 2 and 3 (see Appendix 2). The regression coefficients and significance of the main explanatory variables in the results of the robustness test are generally consistent with the regression results reported in our study (see Table 5). This supports the robustness of our results.

Third, following Cai *et al.* (2020), we also classified our sample into three categories based on the duration of the design from the submission data to the data we collected. For instance, we reclassified the sample into different time periods, namely, a time period less than 250 days (Sample 1), between 250 days and 500 days (Sample 2) and more than 500 days (Sample 3), and formulated new regression models using the reclassified sample. The results show that the coefficients and significance of the main explanatory variables are generally consistent with the original results (see Appendix 3), further confirming the robustness of our results.

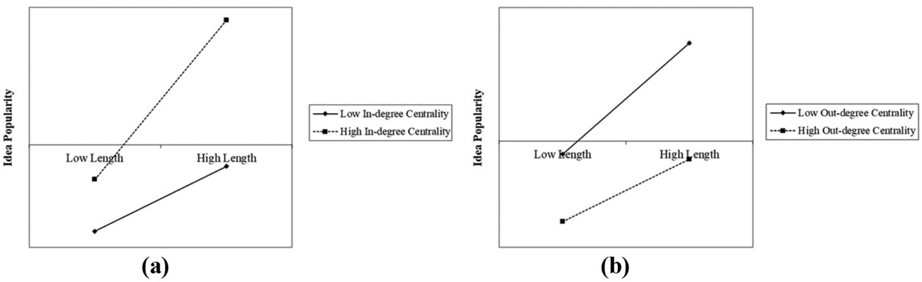
Conclusions and discussion

Despite the increasing prevalence of user engagement in company-hosted OICs, scant studies have explored how users can increase the popularity of their design ideas in OICs. Drawing on persuasion theories and social network analysis, we found that the volume, valence, variance and length of user reviews all positively influenced idea popularity in an



Notes: (a) Variance* in-degree centrality; (b) variance* out-degree centrality

Figure 2. Interaction between degree centrality and review variance



Notes: (a) Length* in-degree centrality; (b) length* out-degree centrality

Figure 3. Interaction between degree centrality and review length

OIC. Our study also found that a user's in-degree centrality (i.e. their number of followers) had a positive impact on idea popularity, while his/her out-degree centrality (i.e. their number of followings) exerted a negative impact. Moreover, the interaction effects between degree centrality and online reviews were also confirmed in our study. Specifically, in-degree centrality was found to positively interact with review valence, review variance and review length to influence idea popularity, while out-degree centrality negatively interacted with review valence, review variance and review length to influence idea popularity.

Theoretical contributions and practical implications

This study contributes to the open innovation and social network literature in several respects. First, while some prior studies have tapped into the determinants of idea popularity in OICs, these studies have largely focused on factors that are in relation to the characteristics of users and ideas. Nevertheless, limited attention has been paid to exploring the collective influence by other users on idea popularity (Yang and Han, 2021; Zhu *et al.*, 2019). In other words, the impact of OIC reviews on idea popularity is under-explored. Drawing on the interactive marketing perspective, our study uses a large sample from the LEGO community and examines user design and idea popularity from a community member's point of view (Akman *et al.*, 2019). In so doing, our study responds to the call for research on customer interactivities in various social media platforms (Lim *et al.*, 2022) and extends the application of the interactive marketing literature to the open innovation context.

Second, this study is an important complement to the few existing studies on idea popularity from a social network perspective (Akman *et al.*, 2019). Surprisingly, the existing literature has neglected the fact that OICs are socially interactive communities in which a user's position or standing within the network plays a significant role in influencing other members' perceptions and behaviors. As a result, they have largely ignored the social nature of OIC members and peer influence within OICs (Yang and Han, 2021). From a social network perspective, our study is the first to confirm the role of online reviews and user network centrality in influencing idea popularity in OICs. Thus, our study not only extends the application of persuasion theories and online review perspectives to the open innovation literature but also opens a novel avenue for future open innovation research that might investigate idea popularity and implementation from a social network point of view.

Third, by integrating social network analysis (Wellman, 1983) and persuasion theories (Funkhouser, 1984), we also confirmed the interaction effects of review characteristics and users' social network centrality on idea popularity. This compensates the lack of existing literature on the interaction effects of online reviews and the social network on idea popularity in the open innovation literature. Our study finds that a user's social network centrality not only directly influences idea popularity but also interacts with review characteristics to influence the latter, while our findings shed additional empirical light on factors determining idea popularity and their relative impact on idea popularity.

Our findings also generate practical implications not only for OIC users but also for companies hosting OICs. First, our finding that the characteristics of reviews a user design receives from OIC members have a significant impact on idea popularity provides clear evidence for the power of online reviews. The finding suggests that when users post their design ideas in an OIC, they should take reviews seriously and actively interact with other users, given that key review characteristics (namely, review valence, variance, length and volume) can all drive idea popularity. To increase the volume of reviews, users could discuss their professional product design knowledge and/or share the journey of a given design with other users to attract more attention from OIC users. Moreover, high review variance may enhance the perceived uniqueness of a design idea (Wu *et al.*, 2021) and thereby increase idea popularity. As such, we recommend users not deliberately discourage dispersed reviews. Rather, they should take this as a good opportunity not only to draw more attention from other users by actively responding to different opinions but also to improve the quality of designs by picking up valuable feedback and suggestions from OIC members. However, this does not mean that users could ignore the negative comments received. Rather, they still need to respond strategically to negative reviews and try to maintain a high volume of positive reviews.

Second, our study also provides clear evidence for the usefulness of using online voting and reviewing systems. Our findings serve as a signal to companies hosting OICs that they should encourage their members to engage in peer evaluation of user designs in a more meaningful way. For instance, companies are advised to form a review ranking system for each design idea and a reviewer ranking system for OIC reviewers. These ranking systems could clearly distinguish between high- and low-quality reviews. To encourage more constructive comments, it is further recommended that companies reward OIC users whose reviews are highly ranked by other users. This strategy may motivate OIC members not only to provide lengthy and informative reviews to enhance the overall quality of their reviews but also encourage them to post unique feedback or suggestions that inspire users to improve their design ideas. Furthermore, our study suggests companies consider idea evaluation from OIC members' social interactions as an inference to better identify which design ideas are popular among OIC members and thus improve the effectiveness and efficiency of future idea selection and implementation.

In addition, empirical evidence for the interaction effects between degree centrality and online reviews to influence idea popularity can serve as a warning sign for companies to pay more attention to users with lower degree centrality within their network, e.g. new OIC users. For example, among users who struggle to make their creative design ideas stand out from the crowd, OICs should provide useful guidelines for increasing their in-degree centrality to expand their user base and publicize their creative designs to a larger audience. As a result of these actions, their designs could attract more attention from other users, promote further user engagement and generate a buzz in an OIC, leading to increased idea popularity.

Limitations and future research directions

There are several limitations of this research which may provide directions for future research. First, our data was collected solely from a single open innovation platform. Although we view the LEGO community as very representative of firm-hosted OICs, it is possible that user behaviors on different open innovation platforms may be very different. Thus, we recommend that future research extends the current study to other OIC contexts to improve the generalizability of our results. Second, our study used a cross-sectional design, which provided a very static view of our research question and may lead to concerns about our causality inference. Although our post-hoc analysis supports the robustness of our analysis, it is recommended that future research adopt a longitudinal research design to improve the causality inference. Third, the data used in this research were at an aggregated level, which cannot capture the heterogeneity of users. Future studies are thereby recommended to examine idea popularity at a more granular (e.g. individual user) level. Fourth, our results show that in-degree centrality negatively interacts with review volume to influence idea popularity. It is possible that in-degree centrality directly influences review volume and thus increase idea popularity. We recommend future research extends the current study to further explore the relationship among in-degree centrality, review volume and idea popularity. Fifth, this research explored only the interaction effects of users' degree centrality and online reviews on idea popularity. Future studies are therefore recommended to identify other moderation mechanisms that may influence how idea popularity is achieved in an OIC. In addition to the influence of reviews and social relations, idea popularity may also be affected by individual factors such as cognitive needs, emotional needs and information processing ability. For instance, studies have suggested that online reviews may have a different impact on social media users insofar as some users are more sensitive to informational influence from OIC users, while others are more susceptible to social influence (Aral and Walker, 2012). Therefore, we recommend future research combines additional individual factors to extend understanding of how idea popularity can be achieved in OICs.

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Appendix 1

Variables	Model 1	Model 2	Model 3
Control variables			
No. of designs	0.036** (0.014)	−0.029*** (0.010)	−0.081*** (0.011)
Experience	−0.207*** (0.013)	−0.045*** (0.009)	−0.045*** (0.009)
Time	0.017(0.012)	0.011(0.009)	0.009(0.008)
No. of pictures	0.112*** (0.013)	0.015(0.009)	0.008(0.009)
Length of description	0.054*** (0.014)	−0.014(0.010)	−0.008(0.009)
No. of update	0.287*** (0.015)	0.036*** (0.011)	0.043*** (0.010)
Independent variables			
Review volume		1.057*** (0.017)	1.010*** (0.018)
Review valence		0.104*** (0.015)	0.122*** (0.014)
Review variance		0.063*** (0.016)	0.080*** (0.015)
Review length		0.130*** (0.010)	0.107*** (0.010)
Moderators			
In-degree centrality			0.136*** (0.019)
Out-degree centrality			−1.170*** (0.072)
Volume * In-degree centrality			0.030*** (0.005)
Valence* In-degree centrality			0.202*** (0.021)
Variance* In-degree centrality			0.128*** (0.023)
Length* In-degree centrality			0.052*** (0.008)
Volume * Out-degree centrality			−0.008*** (0.003)
Valence* Out-degree centrality			−0.082*** (0.026)
Variance* Out-degree centrality			−0.033(0.026)
Length* Out-degree centrality			−0.023(0.014)
Cons	−0.007	0.023	−0.044
Adjusted R^2	0.195	0.610	0.664
AIC	10812.760	7579.105	6916.608
BIC	10857.610	7649.574	7051.140

Notes: ***$p < 0.01$; **$p < 0.05$; and *$p < 0.1$. Standard errors in parentheses. AIC = Akaike information criterion; BIC = Bayesian information criterion

Table A1. Robustness test results (winsorization)

Appendix 2

Variables	Model 1	Model 2	Model 3
Control variables			
No. of designs	0.030** (0.013)	−0.002(0.012)	−0.071*** (0.014)
Experience	−0.223*** (0.019)	−0.102*** (0.018)	−0.093*** (0.018)
Time	0.019(0.014)	0.012(0.011)	0.008(0.010)
No. of pictures	0.120*** (0.016)	0.046*** (0.013)	0.030** (0.012)
Length of description	0.044*** (0.016)	−0.004(0.013)	−0.003(0.013)
No. of update	0.266*** (0.034)	0.076*** (0.024)	0.071*** (0.024)
Independent variables			
Review volume		0.528*** (0.080)	0.560*** (0.130)
Review valence		0.133*** (0.015)	0.167*** (0.019)
Review variance		0.095*** (0.014)	0.118*** (0.018)
Review length		0.190*** (0.019)	0.163*** (0.019)
Moderators			
In-degree centrality			0.144*** (0.036)
Out-degree centrality			−0.172*** (0.058)
Volume * In-degree centrality			−0.041(0.043)
Valence* In-degree centrality			0.349*** (0.065)
Variance* In-degree centrality			0.221*** (0.051)
Length* In-degree centrality			0.069** (0.033)
Volume * Out-degree centrality			0.005(0.005)
Valence* Out-degree centrality			−0.261** (0.105)
Variance* Out-degree centrality			−0.156** (0.073)
Length* Out-degree centrality			−0.046(0.032)
Cons	2.49e-08	1.50e-08	−0.013
R^2	0.186	0.475	0.547

Notes: ***$p < 0.01$; **$p < 0.05$; and *$p < 0.1$. Standard errors in parentheses

Table A2. Robustness test results (generalized method of moments)

Appendix 3

Variables	Model 1	Model 2	Model 3
Control variables			
Sample 1, $N = 2{,}576$			
No. of designs	0.015(0.018)	−0.014(0.015)	−0.077*** (0.016)
Experience	−0.223*** (0.017)	−0.092*** (0.015)	−0.090*** (0.014)
Time	−0.006 (0.033)	0.009(0.027)	0.006(0.026)
No. of pictures	0.117 *** (0.018)	0.053*** (0.015)	0.045*** (0.014)
Length of description	0.060*** (0.018)	−0.003(0.015)	−0.002(0.014)
No. of update	0.215 *** (0.018)	0.053*** (0.015)	0.051*** (0.015)
Independent variables			
Review volume		0.626*** (0.019)	0.622*** (0.022)
Review valence		0.135*** (0.023)	0.170*** (0.023)
Review variance		0.097*** (0.023)	0.125*** (0.023)
Review length		0.159*** (0.015)	0.139*** (0.015)
Moderators			
In-degree centrality			0.148*** (0.025)
Out-degree centrality			−0.241*** (0.042)
Volume * In-degree centrality			−0.011 (0.015)
Valence* In-degree centrality			0.352*** (0.042)
Variance* In-degree centrality			0.253*** (0.043)
Length* In-degree centrality			0.040*** (0.016)
Volume * Out-degree centrality			0.004 (0.005)
Valence* Out-degree centrality			−0.378*** (0.072)
Variance* Out-degree centrality			−0.248*** (0.057)
Length* Out-degree centrality			0.002(0.032)
Cons	−0.020	0.004	−0.013
Adjusted R^2	0.171	0.461	0.515
AIC	6562.200	5459.484	5195.113
BIC	6603.178	5523.878	5318.047
Sample 2, $N = 1{,}795$			
Control variables			
No. of designs	0.054** (0.022)	0.015(0.017)	−0.052*** (0.017)
Experience	−0.228*** (0.023)	−0.111*** (0.019)	−0.096*** (0.017)
Time	−0.013(0.064)	0.023(0.051)	0.042(0.045)
No. of pictures	0.124*** (0.024)	0.043** (0.019)	0.014(0.017)
Length of description	0.020(0.025)	−0.016(0.020)	−0.001(0.018)
No. of update	0.327*** (0.022)	0.102*** (0.019)	0.092*** (0.017)
Independent variables			
Review volume		0.461*** (0.016)	0.493*** (0.021)
Review valence		0.122*** (0.031)	0.118*** (0.029)
Review variance		0.089*** (0.031)	0.091*** (0.031)
Review length		0.216*** (0.020)	0.180*** (0.018)
Moderators			
In-degree centrality			0.083*** (0.026)
Out-degree centrality			−0.112** (0.056)

(*continued*)

Table A3. Robustness test results (classified the sample)

Variables	Model 1	Model 2	Model 3
Volume * In-degree centrality			0.032** (0.013)
Valence* In-degree centrality			0.414*** (0.042)
Variance* In-degree centrality			0.265*** (0.047)
Length* In-degree centrality			0.052*** (0.018)
Volume * Out-degree centrality			−0.302*** (0.041)
Valence* Out-degree centrality			−1.034*** (0.169)
Variance* Out-degree centrality			−0.706*** (0.250)
Length* Out-degree centrality			−0.048** (0.024)
Cons	0.027	−0.021	−0.066
Adjusted R^2	0.208	0.504	0.608
AIC	4897.742	4062.507	3650.189
BIC	4936.192	4122.927	3765.537
Sample 3, N = 104			
Control variables			
No. of designs	0.025(0.085)	−0.080(0.061)	0.062(0.065)
Experience	−0.176(0.116)	0.043(0.087)	0.011(0.065)
Time	−0.240(0.267)	−0.066(0.191)	0.079(0.151)
No. of pictures	0.154(0.122)	−0.096(0.091)	−0.022(0.071)
Length of description	0.095(0.145)	0.051(0.102)	−0.025(0.077)
No. of update	0.621*** (0.177)	0.375*** (0.129)	0.208** (0.099)
Independent variables			
Review volume		1.376*** (0.170)	1.601*** (0.247)
Review valence		0.136(0.132)	−1.545*** (0.485)
Review variance		0.004(0.167)	−1.245*** (0.345)
Review length		0.354*** (0.095)	1.358*** (0.242)
Moderators			
In-degree centrality			−0.646** (0.262)
Out-degree centrality			−1.254(1.955)
Volume * In-degree centrality			0.225(0.274)
Valence* In-degree centrality			1.060*** (0.366)
Variance* In-degree centrality			1.122*** (0.314)
Length* In-degree centrality			0.155(0.186)
Volume * Out-degree centrality			1.329(2.223)
Valence* Out-degree centrality			−27.208*** (6.832)
Variance* Out-degree centrality			−22.083*** (4.585)
Length* Out-degree centrality			14.899*** (3.585)
Cons	0.805	0.418	−0.259
Adjusted R^2	0.149	0.581	0.778
AIC	311.691	241.540	183.764
BIC	330.202	270.628	239.297

Notes: ***p < 0.01; **p < 0.05; and *p < 0.1. Standard errors in parentheses. AIC = Akaike information criterion; BIC = Bayesian information criterion

Table A3.

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