Lead Users as Idea Supplier in Online Community Platform: How to Choose the Right Ideas to Implement?

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Abstract

Crowdsourcing ideas from users in online communities are becoming common practice in the development of high-tech products. While most studies focus on sourcing ideas from ordinary users (i.e., non-experts), high-tech firms commonly rely more on 'lead users'. Despite the importance of lead users' peer-evaluation activities on a firm's user community platform, research on the relationship between these activities and a firm's actual implementation decision is scarce. We draw on lead user theory and a large dataset from a high-tech firm's platform to examine whether an idea's popularity, the comments it receives and sentiment are good predictors of a firm's consideration and implementation decisions. We find that in addition to the number of votes and comments, sentiment is a predictor of an idea's further development and implementation. Furthermore, implementing a lead user's ideas decreases the user's motivation marginally to contribute continuously to the platform. These findings have implications for the design and operations management of user community platforms.

Keywords: User community, lead user, idea selection, crowdsourcing, platform

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1. Introduction

The advent of advanced digital technologies provides opportunities for organisations to establish successful platform-based business operations (Gawer & Cusumano, 2008). Digitalisation allows firms to develop online platforms that enable them to provide customers with instantaneous access to products and services, solicit inputs for innovation, and engaging multiple parties as complementors in product development (Nambisan, Siegel, & Kenney, 2018). Firms are finding inputs from external sources useful for innovation as contributions from these sources minimise the uncertainties associated with developing market-relevant products (Herstatt, Verworn, & Nagahira, 2004; Podolny, 1994; West & Bogers, 2014). Amongst these sources, users are significant contributors to novel inputs for product development because they possess relevant information about market needs (Chatterji & Fabrizio, 2014). As such, large organisations are building platform-based online user communities (e.g. My Starbucks Idea, Dell Ideastorm) as a means to source inputs from their users to develop products, services and processes (Ebner, Leimeister, & Krcmar, 2009; Mahr & Lievens, 2012).

Research in crowdsourcing shows that firms utilise online user communities as platforms to solicit and create inputs for product development in diverse industries such as retail, computer, and food and beverage (Bayus, 2013; Nishikawa, Schreier, & Ogawa, 2013; Schemmann, Herrmann, Chappin, & Heimeriks, 2016; Yang & Han, 2019). Crowdsourcing hinges on the notion that the abilities of a large group of people exceed that of an individual subject-matter expert (Felin, Lakhani, & Tushman, 2017; Galton, 1907). As such, firms are encouraged to work with large groups of people outside the organisation to source for innovative ideas and implement these ideas during new product development (NPD). In a user community platform, participants self-select to join the community, contributing their ideas, feedback, and comments, at times without expecting any explicit benefit in return, apart from the potentiality that the firm will use their inputs to develop new products (Ooi & Husted, 2016; Poetz & Schreier, 2012).

Studies in user communities tend to focus on engaging non-expert users (i.e. ordinary users) in NPD (Bayus, 2013; Füller, Jawecki, & Mühlbacher, 2007; Poetz & Schreier, 2012). However, studies show that user community platforms of emerging technological organisations often rely on a distinctively different group of users called "lead users" to participate in NPD (Mahr & Lievens, 2012). Lead user theory suggests that these users excel in providing essential inputs for NPD because of their technical abilities and advanced market needs, which lead to the development of radical products (Hienerth & Lettl, 2017; Lettl, Hienerth, & Gemuenden, 2008). Lead users' superior technical abilities and market knowledge make them invaluable contributor to a firm's product development activities. Lead user studies focus on explaining the motivation behind lead user's willingness to participate in user communities, the lead user product development process, and efficiency of user communities in developing innovations when compared with firm's efforts (Hienerth, von Hippel, & Berg Jensen, 2014; Lettl et al., 2008; Nambisan & Baron, 2009).

While researchers into user communities agreed that lead users are important suppliers of innovative ideas to firms, leading to the development of technological products for high-tech firms (Hult, Ketchen, & Slater, 2004; Kim & Chai, 2017); there is a lack of attention given to examine the importance of these lead users within the wider organisational supply-chain network. Specifically, research into the link between lead user's contributions in user communities and the actual implementation of these ideas is still scarce. Hence, in this study, we examine the underlying factors affecting a firm's implementation decisions and whether these decisions, in turn, motivate lead users to contribute more in user communities.

Our research question addresses a long-held assumption in the user communities literature that assumes a firm's success in engaging lead users in user community platform would lead to the implementation of their contributions in NPD. This assumption is problematic because it relies on the notion that participants, through idea proposition and peer-reviewing activities on the platform, will eventually have their ideas implemented by the firm (Mahr & Lievens, 2012; Nambisan & Baron, 2009). Relatedly, the NPD literature suggests that the implementation of any ideas during product development largely hinges on whether these ideas overcome the rigorous stage-gates within a firm (Cooper & Sommer, 2016). Moreover, as a firm requires various interrelated processes and capabilities during NPD (Eisenhardt & Martin, 2000; Leonard-Barton, 1992; Ooi & Husted, 2021), an idea's survival of the peer-reviewing process on the platform does not guarantee its survival in the firm's stage-gates nor that the firm will develop the idea further.

Importantly, to address this research gap, we conducted an empirical study using data from Microsoft Power Business Intelligence (PowerBI) user-innovation platform. We focus on understanding the relationships between comments and votes with the firm's decision to implement an idea; and subsequently, whether the implementation decision of an idea triggers further activities from lead users. Our results show that votes and comments are good predictors of an idea's implementation but ironically, seeing their ideas implemented marginally decreases a lead user's motivation to contribute more ideas on the platform.

Our study contributes to the crowdsourcing and user community platform literatures by providing insights into designing user community platform and managing lead user participation in NPD (Nambisan et al., 2018; Stanko, Fisher, & Bogers, 2017). Exploring the relationship between lead user's contributions and the actual implementation of these ideas in a firm's NPD is the first step toward evaluating the effectiveness of the user community platform in supplying innovative and development-worthy product ideas for high-tech firms (Kim & Chai, 2017). Furthermore, linking whether the implementation of these ideas motivates lead users to continuously supply ideas enable us to offer insight into managing complex lead user behaviour in firm-sponsored platforms more effectively.

2. Literature Review and Hypothesis Development

The online-based user community is a digital platform that connects users with other users and a focal firm to share information, feedback, and ideas. Crowdsourcing product ideas from users are valuable as studies show that user inputs contribute to NPD, resulting in incremental and radical innovations (Ooi & Husted, 2016; Poetz & Schreier, 2012). The notion of crowdsourcing is to source for ideas from external actors (i.e. the crowd) as ideas from the crowd are likely to outperform that of subject-matter experts (Galton, 1907). User community platform, as a form of crowdsourcing, allows a firm to solve complex problems by drawing on the hidden knowledge of its users to derive innovative solutions (Bayus, 2013; Felin & Zenger, 2014). Commonly organised as a firm-managed or user-managed platform (Chen, Pereira, & Patel, 2020), the main activities on these platforms are to submit feedback on usage experience, product ideas and evaluate these contributions, and vote on the ideas that users prefer (Hofstetter, Aryobsei, & Herrmann, 2018). These activities create value for a firm as ideas that survive the peer-reviewing process are likely to signal strong market alignment and frequently chosen by the focal firm to proceed to implementation.

Lead user theory (von Hippel, 1986) posits that among the participants of such platforms, a group of users called lead users are more innovative than ordinary users in many ways. According to Magnusson (2009), a user's knowledge about the product and technology affects the types of ideas that the user can supply. This conclusion is in line with the findings of Jeppesen and Frederiksen (2006), where lead users are found to be more innovative and willing to contribute inputs to online communities. Lead users are not merely using products but also possess more advanced knowledge about market needs and the technical expertise to make changes to existing products (Lettl et al., 2008; Lüthje & Herstatt, 2004). As representative user innovators, lead users are capable and motivated to contribute to NPD, making them prime candidates for firms needing to source for radical product ideas that challenge the existing dominant design paradigm (von Hippel, 1986; West & Bogers, 2014). Literature posits that lead users can stay ahead of the market because they possess relevant knowledge of latent needs and trends, and have the necessary technical abilities to make changes to products (Hienerth & Lettl, 2011, 2017; Lüthje & Herstatt, 2004; von Hippel, 1986). Empirical findings from Mahr and Lievens (2012) show that the value of lead users lies in their ability to suggest solutions rather than merely describing problems, which leads to lead users contributing ideas proactively to extend the functionalities of existing products. Relatedly, Bayus (2013) suggest that ideas supplied by lead users are more likely to be implemented compared to those supplied by ordinary users. As opposed to ordinary users, lead users are able to combine their advanced knowledge about market-leading needs with their technical expertise to offer novel solutions (Hienerth et al., 2014; von Hippel, 1986).

Furthermore, research studying lead user motivation indicates that lead users are motivated to contribute ideas during NPD by the expected costs and benefits of deriving the innovative idea. The literature on knowledge stickiness posits that lead users are more likely to supply ideas to the focal firm when the costs of transferring such “sticky” knowledge to the firm are high (Bogers, Afuah, & Bastian, 2010; von Hippel, 1994). As sticky knowledge consists of highly tacit components, it is then more cost-effective for lead users to convert the tacit components into more explicit forms, such as a product idea, before sharing it on the user community platform (Jensen & Szulanski, 2004; Mahr & Lievens, 2012; Ogawa, 1998). Furthermore, if lead users expect to benefit (i.e. meeting their advanced needs) when their ideas are implemented, they would be motivated to contribute ideas to the platform (Lettl, Herstatt, & Gemuenden, 2006). Beyond the obvious benefit of using the new product if their ideas are implemented, Frey, Lüthje, and Haag (2011) suggest that lead users tend to contribute more substantial inputs when they are motivated by the problem-solving process itself. The sheer satisfaction of solving the task is in itself a motivational factor for lead users (Füller et al., 2007; Jeppesen & Frederiksen, 2006). Table 1 summarises the characteristics of lead user and ordinary user involvement in user community platforms.

Table 1: Characteristics of lead user and ordinary user involvement in platforms

	Lead User	**Ordinary User**	**Representative studies**
Examples	LEGO Lead User Lab, Linux, Microsoft PowerBI, P&G connect+develop	Dell IdeaStorm, Porsche 911 Carrera 4S, Starbucks Idea	
Type of knowledge users possess	Technical and “sticky”	Non-technical	Lettl et al. (2008); Magnusson (2009); von Hippel (1986, 1994)
Inputs users provide to firms	Solutions such as ideas for latent needs, prototypes (e.g. product or software), evaluative comments to shape ideas	Problems such as product failure feedback, general ideas	Hienerth and Lettl (2017); Mahr and Lievens (2012); Ooi and Husted (2016); Poetz and Schreier (2012)
Innovation outcome from inputs	Incremental and radical	Incremental	Lettl et al. (2008); Lüthje and Herstatt (2004); West and Bogers (2014)
Motivation to participate	Benefit from using the improved product and enjoyment from the problem-solving process	Benefit from using the improved product	Frey et al. (2011); Füller et al. (2007); Hienerth and Lettl (2017); Jeppesen and Frederiksen (2006); Lettl et al. (2006); Shah (2006)
Propensity of firms implementing proposed ideas	More likely	Less likely	Bayus (2013); Hienerth and Lettl (2011); Poetz and Schreier (2012)

Despite the importance of lead users’ contribution of product ideas in user community platforms to a firm’s NPD; there is still a lack of research into the relationship between these contributions and actual implementation of these ideas. Prior studies suggest that in user community platform, a key role of fellow community participants is to evaluate each other’s product ideas (Füller, 2010; Hienerth & Lettl, 2011; Hofstetter et al., 2018). The ideas garnering the most comments, and ultimately votes are deemed to be popular. However, most studies tend to focus on managing interactions within the community platform to stimulate ideation (Frey et al., 2011; Poetz & Schreier, 2012; Yang & Han, 2019) neglecting the implementation decision of these ideas. Moreover, in the crowdsourcing literature, studies also tend not to delineate between the types of users (Schemmann et al., 2016). Our focus instead, is on the innovative users in a high-tech user community platform, where the users participating in the platform are lead users rather than ordinary users. We extend the notion that lead users are capable of providing solutions during NPD (Hienerth & Lettl, 2011; Mahr & Lievens, 2012), by explicating whether the popularity of a lead user's contributions has any impact on a firm's implementation decisions.

2.1 Votes and Comments Influence Firm's Consideration

As discussed above, voting, commenting and submitting ideas are participants' main activities in an online user community platform. When the user community consists of lead users, lead user theory posits that these ideas are more likely to be implemented by the focal firm. This study is designed to examine this relationship posits by the lead user theory within a user community platform context. First, we investigate whether the popularity of a lead user's idea on a user community platform impacts the focal firm's tendency to shortlist the idea. Second, we examine if popularity also impacts the propensity for the focal firm to actually implement the idea. Third, we investigate whether having their ideas implemented by the focal firm will affect lead users' tendency to contribute on the platform.

Effectively, we adopt the lead user theory proposition that lead user's inputs tend to be implemented by the focal firm (Bayus, 2013; Jeppesen & Frederiksen, 2006; Mahr & Lievens, 2012), and measure these inputs as votes and comments. Specifically, we measure the quantity and sentiment (i.e. positive or negative) of these inputs. Two measures related to lead users' tendency to actively participate on the platform are adopted, which are idea generation and commenting behaviour (Hienerth & Lettl, 2017; von Hippel, 1986). Details about the hypotheses and their development are presented below.

In user community platforms, lead users contribute in the form of new ideas, evaluative comments on other submitted ideas, and voting for ideas that best meet the (perceived) needs of (lead) users (Foss, Jeppesen, & Rullani, 2020). Commenting and voting are common mechanisms used on user community platforms to develop and screen ideas. Prior studies in lead user theory indicate that ideas garnering the most comments and votes from other users are more likely selected by the firm for further development as comments and votes signal quality of these ideas (Füller, 2010; Hofstetter et al., 2018; Schemmann et al., 2016). However, voting has its pitfalls in the form of reciprocal voting, where a popular idea on the platform might not be the best solution (Hofstetter et al., 2018). Notwithstanding the potentiality of reciprocal behaviour, Magnusson, Wästlund, and Netz (2016) conclude that in the absence of professional experts, firms can safely rely on lead users to evaluate and screen ideas submitted to online communities as long as firms provide clear criteria for assessment. One could argue that engaging lead users in this process could minimise the risks of reciprocal behaviour during idea evaluation. This is because lead users tend to draw on their technical knowledge when evaluating the submitted ideas instead of plainly relying on the voting and commenting behaviour of other users on the platform (Hienerth et al., 2014; Nishikawa et al., 2013; Poetz & Schreier, 2012). Moreover, lead users are motivated to participate in online user community to derive benefit from successful ideas, as such, they are likely to offer inputs that are genuinely aimed at choosing ideas that best meet their needs (Hienerth & Lettl, 2017; von Hippel, 1986).

In addition to expected benefit, lead users are motivated deeply by the pleasure of solving problems. They tend to provide positive and negative constructive comments with the aim of evaluating and shaping these submitted ideas (Frey et al., 2011; Füller et al., 2007; Jeppesen & Frederiksen, 2006; Ooi & Husted, 2016). As we discussed above, giving evaluative comments to ideas proposed by other community users is a common activity for participants of user community platform. Lead users are excellent candidates to comment and develop these ideas further as they possess the necessary technical skills (Hofstetter et al., 2018; Lettl et al., 2008; Mahr & Lievens, 2012). Hence, we hypothesised the following:

Hypothesis 1a: for the ideas generated by lead users, the more votes they received, the more likely they are to be considered by the firm.

Hypothesis 1b: for the ideas generated by lead users, the more comments they received, the more likely they are to be considered by the firm.

Naturally, H1b seem to suggest that a firm will automatically consider an idea generated by a lead user if the idea receives sufficient votes and comments from other lead users in the online community (Hofstetter et al., 2018). This is not always true as objective measurements such as number of votes and comments disregard the more subjective notion of sentiment. Thus, it is insufficient to rely solely on these measurements as predictors of an idea's likelihood to be considered by the firm. Earlier studies have suggested that linguistic cues in submitted ideas and evaluations predict an idea's quality to firms (Coussement, Debaere, & Ruyck, 2017; O'Leary, 2016). It is logical to infer that sentiment could impact a firm's decision to consider an idea. For instance, the firm could perceive an idea that consists mostly of the submitter's complaints as having a negative sentiment, thus, disregarding the idea as nothing but an unsatisfied user's rant rather than a useful idea worthy of the firm's consideration. Likewise, the firm could perceive an idea that receives mostly negative comments from peers as unworthy for further development.

Despite an idea projecting a negative sentiment and even receive negative comments from other lead users, it is important to note that not every negative idea or those attracting negative comments are automatically disregarded by the firm. As sometimes, a firm could see value in scouring negative ideas for useful NPD inputs or negative comments as merely part of the user community's process of the peer-reviewing, screening and shaping of an idea into potentially novel solution (Hienerth & Lettl, 2011; Magnusson et al., 2016). But, a firm could still opinion that negative ideas and those receiving more negative comments are signals that these ideas are of inferior quality; thus they cannot be improved further or be serious contenders for a firm's consideration (Hofstetter et al., 2018; Lettl et al., 2008; Mahr & Lievens, 2012). We take into account the effect of sentiment and a firm's likely perception of negativity to hypothesise the following:

Hypothesis 1c: for the ideas generated by lead users, the more negative they are, the less likely they are to be considered by the firm.

Hypothesis 1d: for the ideas generated by lead users, the more negative of the comments they received, the less likely they are to be considered by the firm.

2.2 Votes and Comments Influence Implementation Decision

Studies in lead user theory have found that ideas generated by lead users in various sectors such as consumer goods and medical technology, to be novel and more likely to meet customers' needs than firm-developed ideas (Herstatt et al., 2004; Lettl et al., 2006; Nishikawa et al., 2013). However, other research shows that these user-generated ideas are less feasible to produce when compared to firm-developed ideas, though not by a considerable margin of difference (Poetz & Schreier, 2012). Furthermore, it is generally found that out of the many ideas posted by lead users in user community platforms, firms can only implement and translate a small amount of these ideas into actual products (Bayus, 2013; Hofstetter et al., 2018). This conclusion from the lead user literature is not surprising because firms have limited resources that they can allocate to acquire ideas from suppliers and implement these ideas into the NPD process (Hult et al., 2004). As such, most firms employ some form of a stage-gate process to screen and select ideas for further development (Cooper & Sommer, 2016). Relatedly, voting and evaluative commenting behaviour by lead users becomes the mechanisms that a firm uses to screen and select ideas for implementation.

Moreover, from our earlier discussion, we know that lead users have superior technical abilities when compared to ordinary users. Therefore, lead users are more likely to generate ideas that are technically feasible for firms to implement (Hienerth & Lettl, 2011; Schweitzer, Gassmann, & Rau, 2014). Technically-sound and feasible ideas are important, especially for high-tech products due to the high technical uncertainties often associated with high-tech products. Ordinary users would find it challenging to provide meaningful and feasible contributions because they do not possess the necessary technical knowledge (Lettl et al., 2008; von Hippel, 1994). Furthermore, lead users also excel at evaluating a high-tech product idea's producibility, given their technical prowess (Hienerth & Lettl, 2011; Magnusson et al., 2016). Thus, an idea that is chosen by fellow lead users in the online community platform is likely to signal to the firm about the idea's potential for development. Building on these arguments, we propose that lead users' technical abilities enable them to not only evaluate and screen novel ideas but also whether these ideas are feasible and producible by the firm. Therefore, we hypothesise that ideas receiving more votes and comments from participants in a user community platform within a high-tech context are more likely to be implemented by the firm.

Hypothesis 2a: for the ideas generated by lead users, the more negative they are, the less likely they are to be implemented by the firm.

Hypothesis 2b: for the ideas generated by lead users, the more comments they received, the more likely they are to be implemented by the firm.

Although the lead user theory posits that ideas surviving the peer-evaluation process are more producible (Schweitzer et al., 2014), there is a need to consider whether sentiment impacts a firm's consideration decision. While an idea could, in general, receive vast amounts votes and comments from other lead users, these measurements are not necessarily good predictors of producibility (Coussement et al., 2017; O'Leary, 2016). It is also impractical for a firm to implement every idea that attracts the highest number of votes and comments in the evaluation process, given the limited resources it possesses (Hult et al., 2004). Hence, a firm will still need to assess whether these 'winning' ideas are worthwhile for further development (Cooper & Sommer, 2016).

Inferring from our discussion above about the role of sentiment, it is predicted that when a firm evaluates these shortlisted ideas, negative sentiment is likely to impact the firm's final implementation decision. A shortlisted idea that the firm perceives as being negative or those receiving more critical comments from peers are likely to signal that the idea is unworthy of development, despite it surviving the peer voting and comment process. For instance, the firm could have selected an idea for further consideration, amid the idea being negative (as we discussed above). But after assessing this idea further, the firm decides that this negative idea is not worthy for implementation. Naturally, a firm's inclination to disregard the negative idea could be due to the perceive lack of useful inputs for NPD. Similarly, the firm could perceive a shortlisted idea that attracts more negative comments as unwanted by peers and should not be implemented. We thus hypothesised the following:

Hypothesis 2c: for the ideas generated by lead users, the more negative they are, the less likely they are to be implemented by the firm.

Hypothesis 2d: for the ideas generated by lead users, the more negative of the comments they received, the less likely they are to be implemented by the firm.

2.3 Implemented Ideas Impact Lead User's Participation

Lead user theory posits that the likelihood for firms to implement popular ideas generated by lead users could spur more activities by the developers of these ideas on user community platforms. This increase in lead users' contributions is because they will benefit from their involvement in a firm's NPD (Frey et al., 2011; von Hippel, 1986). In this case, when firms implement their ideas, lead users can use these outcomes created from their ideas. As we presented earlier, the expected benefit, whether in the form of economic or personal benefits, will motivate lead users to expend efforts in generating and evaluating ideas in user community platforms (Hienerth & Lettl, 2017; Lettl et al., 2006). Although these benefits are often described as innovation-related benefits, such as the benefit of using the outcomes created through a collaborative NPD process; however, these benefits are also incentive-related

(Bogers et al., 2010). The consensus in lead user theory is that lead users' main incentive is their intrinsic motivation to participate through the contribution of ideas and comments in user community platforms (Frey et al., 2011; Füller et al., 2007; Jeppesen & Frederiksen, 2006). Intrinsic motivation is the enjoyment that lead users feel from the process of solving problems (Bogers et al., 2010; Füller et al., 2007) such as developing new software codes and service ideas for websites (Schuhmacher & Kuester, 2012; Shah, 2006).

Prior studies drew links between intrinsic motivation and lead users' participation in innovation activities, where empirical validation of this relationship focused on factors impacting the environment within the user community platform that stimulated participation (Füller, Hutter, & Faullant, 2011; Jeppesen & Frederiksen, 2006). Additionally, the recognition these users obtain when the firm implement their ideas would likely incentivise them to contribute even more ideas (Barnes, Hollenbeck, Jundt, DeRue, & Harmon, 2011). Hence, we can postulate that lead users' continued contribution in a user community platform is likely to increase if firms implement their ideas. This proposition is fuelled by the expected benefits that lead users will obtain when their ideas are converted into new features or products, with the benefits derived from usage (Hienerth & Lettl, 2017; von Hippel, 1986). Given the positive externalities that lead users are likely to experience within the user community platform with every successful implementation of their ideas (Barnes et al., 2011; Gambardella, Raasch, & von Hippel, 2016; Liebowitz & Margolis, 1994); these users will continue to submit ideas to the platform and provide evaluative comments on ideas submitted by other lead users (Bogers et al., 2010; Hienerth & Lettl, 2017). Furthermore, when their ideas are implemented, lead users tend to see this as a positive outcome and opportunity to further showcase their trend-setting and technical prowess (Foss et al., 2020); which will motivate them to offer more ideas and comments. Therefore, we have the following hypotheses.

Hypothesis 3a: lead users with more ideas implemented are more likely to generate more ideas.

Hypothesis 3b: lead users with more ideas implemented are more likely to provide more comments.

The hypotheses above test the underlying factors affecting a firm's consideration and implementation decisions and whether these decisions, in turn, motivate lead users to contribute more in user communities. The key constructs and the hypotheses developed above are summarised in Figure 1.

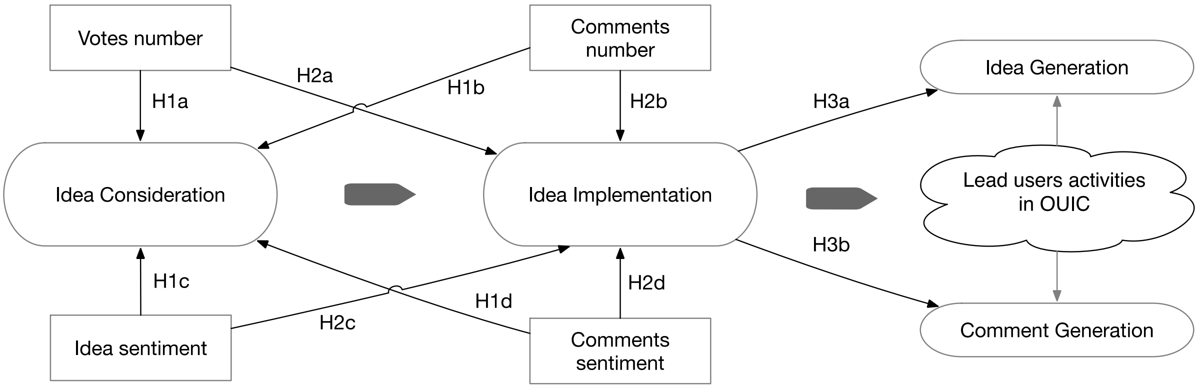

Figure 1. Research model

3. Methodology

3.1 The dataset

We used publicly available data from an online user-innovation platform founded by Microsoft, specifically for the PowerBI software products. The collected data sample from the platform is suitable for our research as the platform is well established with a large number of users actively contributing to product development (Parry, Farndale, Brewster, & Morley, 2021). Furthermore, the data size, i.e., the whole 11985 records of ideas collected in four years by a Python-programmed web scrapper, is appropriate for obtaining insightful results. The platform brings the firm and its users together, collecting ideas directly from PowerBI users on improving existing products and services as well as developing new ones. To participate, users join the platform free of charge by creating a profile with an email address. The platform assigns a default username, i.e., anonymous if users do not provide one when their accounts are created, and users are allowed to change their username at a later stage. Similar to other popular crowdsourcing platforms, such as Dell IdeaStorm and MyStarBucksIdea, the demographics of users are not collected, and the usernames are the identifiers to determine which idea is contributed by whom.

When posting an idea, users are required to provide a title and a description. Besides posting ideas, users can interact with other users by voting whether they support an idea and commenting on others' ideas. A user can give maximum one vote to each idea. If a user votes an idea, then the platform shows that the idea receives "1" vote. Thus, the number of votes received by an idea represents how many users have voted for supporting the idea. Note that as usernames are not associated with votes, we are not able to count how many votes a user provided but how many votes each idea had received as the number of votes is recorded at the idea level. On the contrary, the comments an idea receives are associated with usernames. Therefore, both the number of comments an idea had received and the number of comments an individual lead user had contributed are counted.

The idea review team of Microsoft makes implementation decisions on the posted ideas in two phases. Firstly, the team read ideas and identify the candidate ideas which they need to act on. These candidate ideas are assigned with a label to indicate their status. There are eight status categories, including backlog, under review, escalated, planned, started, consideration for backlog, not planned, and completed. Besides the status label, the team provide a comment to the user in order to explain why a specific label is assigned. The comment may also contain answers to queries if posted together with the idea. In the second phase, the review team works on the identified candidate ideas and adjust the status labels if progress has been made. For instance, the 'under review' label of an idea can be replaced by 'started' if the idea is put into the implementation process. If an idea gains priority after the review, the label 'escalated' will be assigned. Once the implementation is completed, ideas are assigned with 'completed' status. Unlike Dell IdeaStorm, there is no reward (e.g., money, badge) for users if their ideas are implemented.

The PowerBI platform received its first idea in September 2014. We crawled data on all the ideas posted between September 2014 and September 2018 by a Python-programmed web scrapper. In order to stabilise the interaction around a new idea and leave enough time for the firm to complete the review process, we dropped the ideas posted in the last three months, namely July, August and September 2018. To distinguish and select the lead users from all users in the collected dataset, we rely on the 'expert' badge assigned by the platform. The badge is introduced to recognise users who post meaningful ideas and comments, and to encourage sharing of expertise in the platform. More specifically, obtaining the 'expert' badge requires a high level of technical abilities and idea contribution towards products, making these users match the criteria of lead users (see Table 1: (Mahr & Lievens, 2012). Therefore, we filtered out users who do not have the 'expert' badge, leaving the rest of the dataset contains only the ideas posted by lead users, and the interactions among lead users. To improve the readability of the paper, we use 'lead users' and 'users' interchangeable in the rest of the section.

During the data collection period (i.e., Sep 2014 – Jun 2018), 11985 ideas were posted by lead users, out of which 912 ideas had been selected as candidate ideas, and 657 ideas had been implemented. The implementation ratio is 5.48%, which is consistent with other idea crowdsourcing platforms (Di Gangi & Wasko, 2009). As the ideas contributed by the users with username anonymous cannot be distinguished from each other, we dropped the records on the ideas posted by anonymous users. The number of ideas becomes 9135, and 5365 lead users contributed these ideas.

3.2 Related Measures

The dependent variables W_{cand} and W_{impl} are defined to capture whether an idea had been selected as a candidate idea and had been implemented as discussed in hypotheses H1 and H2, respectively. More specifically, both W_{cand} and W_{impl} are dummy variables: W_{cand} is coded as one if an idea had been selected as a candidate. Because the implementation of an idea involves a process, W_{impl} is coded as one if the status label assigned by Microsoft review team is ‘completed’, ‘started’, or ‘escalated’; otherwise, it is coded as zero. The independent variable *number of votes* (n_{votes}) is used to measure how many votes an idea had received. It is a continuous variable. Similarly, we have another continuous independent variable *number of comments* (n_{cmt}) which counts how many comments an idea had received. The value of the variable is zero if no comment had been received.

To test hypotheses H1c, H1d, H2c and H2d, we consider the sentiment of idea texts and comments which may also affect the consideration and implementation of posted ideas. The sentiment scores of idea texts and comments are calculated using the *sentiment()* function from the *sentimentr* package in *R*. As more than one comments are observed for most of the ideas, we calculate the average score of comments to measure the sentiment scores of comments.

Concerning the hypothesis H3, the measures are defined at the user level. Because there is time-dependency existing between the number of ideas a lead user had contributed and the number of ideas the lead user had got implemented, we introduced a time variable t_{k} $(k \geq 0)$ to capture the time-dependent relationships. More specifically, we denote t_0 as the time when the first idea was posted by a lead user, t_1 as the first time when an idea posted by the lead user was implemented by the firm. Thus, we have t_{k} denotes the kth time when an idea posted by the lead user was implemented by the firm where k is in the range of $[0, \mathrm{m}]$ and m represents the total number of ideas the lead user posted were implemented by the firm during the data collection period. Using t_{k}, we transformed the single observation for an individual lead user in our collected data sample into m observations. In the situation where a lead user has no idea implemented, m equals zero meaning that the number of observations after the transformation stays as the original, i.e., at one. The dependent variable *number of ideas generated by a lead user* in the time period between $t_{\text{k-1}}$ and t_{k} (denoted as $n_{\text{ideas\_lead}<t_{\text{k-1}}, t_{\mathrm{k}}>}$) measures the number of ideas a lead user had contributed from time $t_{\text{k-1}}$ to t_{k}, representing the user’s motivation in contributing ideas (see H3a). The other dependent variable *number of* *comments generated by a lead user* the during the period between $t_{k\text{-}1}$ and t_k (denoted by $n_{\text{cmt\_lead}<t_{k-1},\, t_k>}$) is used to measure a user's motivation in generating comments (see H3b). The value of the variable is zero if no comment had been posted by a user during the period between $t_{k\text{-}1}$ and t_k. The independent variable is defined to capture the effect of implementation on users' later innovation behaviours. We define the *number of implemented ideas generated by a lead user* in the period between t_0 and $t_{k\text{-}1}$ as $n_{\text{impl\_lead}<t_0,\, t_{k-1}>}, k \geq 1$. The independent variable represents the lead user's success in generating implemented ideas (see both H3a and H3b). We consider the cumulative number of implemented ideas in the period of t_0 and $t_{k\text{-}1}$ here because existing literature suggests that idea implementation could continue affecting user's innovation contribution (Barnes, Hollenbeck, Jundt, DeRue, & Harmon, 2011). In the case of $k = 0$ when the lead user has no implemented ideas, again, the observation for this user remains as the original. As each of the transformed observations are taken into account as an independent single row in our dataset, we remove the '$<t_0, t_{k\text{-}1}>$' and '$<t_{k\text{-}1}, t_k>$' marks from the variable denotation to improve the readability.

Table 2: Descriptive statistics

	Mean	S.D.	Min	Max
H1 and H2: at idea level				
Whether an idea had been selected as candidate (W_{cand})	0.078	0.268	0.000	1.000
Whether an idea had been implemented (W_{impl})	0.061	0.239	0.000	1.000
Number of votes an idea had received (n_{votes})	136.900	121.056	1.000	392.000
Number of comments an idea had received (n_{cmt})	2.399	15.334	0.000	674.000
Sentiment score of idea	1.293	0.634	-0.518	3.050
Average sentiment score of comments	1.139	0.812	-0.670	2.890
H3: at user level				
Number of ideas generated by a lead user between t_{k-1} and t_k (n_{ideas_lead})	8.455	19.197	1.000	125.000
Number of comments generated by a lead user between t_{k-1} and t_k (n_{cmt_lead})	6.161	18.285	0.000	617.000
Number of implemented ideas generated by a lead user between t_0 and t_{k-1} (n_{impl_lead})	0.269	0.760	0.000	8.000

Table 3: Correlations

H1 and H2	1	2	3	4	5	6
1. Whether an idea had been selected as candidate (W_{cand})	1.000					
2. Whether an idea had been implemented (W_{impl})	0.876***	1.000				
3. Number of votes an idea had received (n_{votes})	0.088***	0.060***	1.000			
4. Number of comments an idea had received (n_{cmt})	0.284***	0.232***	0.068***	1.000		
5. Sentiment of idea	0.075***	0.038***	0.060***	0.064***	1.000	
6. Average sentiment of comments	0.167***	0.335***	0.078***	0.128***	0.237***	1.000
H3	7	8	9			
7. Number of ideas generated by a lead user between t_{k-1} and t_k (n_{ideas_lead})	1.000					
8. Number of comments generated by a lead between t_{k-1} and t_k (n_{cmt_lead})	0.561***	1.000				
9. Number of implemented ideas generated by a lead user between t_0 and t_{k-1} (n_{impl_lead})	0.200***	0.238***	1.000			

***: p-value <0.001

Table 2 provides descriptive statistics for the dependent and independent variables. In our data, an idea received 136.9 votes and 2.399 comments on average. At least one vote was given to each idea, and the maximum number of votes is 392. The minimum number of comments an idea received is zero, and the maximum is 674. Regarding the sentiment of idea and the average sentiment of comments, the mean for these two variables are 1.293 and 1.139 respectively. The portions of the ideas and comments with negative sentiment are both small (i.e., 19.3% and 13.2% respectively).

At the user level, a lead user contributed an average of 8.455 ideas in any time window between $t_{\text{k-1}}$ and t_{k}, and the maximum number of ideas by a single lead user is 125. Regarding implemented ideas, 0.269 ideas were implemented on average in the time window between $t_{\text{k-1}}$ and $t_{\text{k-1}}$, while the maximum is 8, and the minimum is zero. In terms of the number of comments posted by lead users, the mean is at 6.161 with the minimum at zero and maximum at 617. The standard deviation for both dependent variables W_{cand} and W_{impl} are small (see Table 2), indicating that the data points of both measures are close to their mean. The standard deviation for the number of votes and comments an idea had received are 121.056 and 15.334, suggesting that the data points for the votes measure are more spread out. With respect to the standard deviation for the dependent variables in H3, the value for the number of ideas is slightly higher than the number of comments generated by a lead user (i.e., 19.197 and 18.285 respectively as shown in Table 2). However, the mean of the former measure is also slightly higher than the latter (i.e., 8.455 and 6.161), indicating that the variation in both variables is at a similar level.

We first look at the correlative evidence for our hypotheses. We used the Pearson correlation test for all the measures by assuming linear relations among the measures. As shown in Table 3, with respect to H1 and H2, the dependent variables Whether an idea had been selected as a candidate and Whether an idea had been implemented both have a significant positive relationship with the independent variables ($p < .001$). Moreover, for H3, a positive correlation is also detected between the dependent variables and the independent variable ($p < .001$).

4. Results

We test H1 and H2 with a logistic regression approach because the dependent variables W_{cand} and W_{impl} are dummy variables. For H1, consider a logistic model with two independent variables n_{votes} and n_{cmt}, and one dummy dependent variable W_{cand}, we define $p = P(W_{\text{cand}} = 1)$. By assuming a linear relationship between the independent variables and the log-odds of the event that $W_{\text{cand}} = 1$ (i.e., an idea is selected as a candidate idea), we have the following equation (Model 1) to capture the linear relationship:

$$\log_b \frac{p}{1-p} = \beta_0 + \beta_1 n_{\text{votes}} + \beta_2 n_{\text{cmt}}, \qquad (1)$$

where b is the base of the logarithm and $\beta_{0,1,2}$ are the parameters of the model.

As shown in Table 3, the relationship between W_{cand} and n_{votes} is significant and positive (i.e., 0.002), supporting H1a. The coefficient suggests that for every one change in the number of votes an idea received, the log-odds of the idea being considered by the firm as a candidate idea increases by 0.002. A significant positive relationship is also detected between W_{cand} and n_{cmt}, which supports H1b. As the coefficient (i.e., 0.075) is greater than the one for n_{votes}, increasing the number of comments for an idea is more likely to increase the probability that the idea is considered by the firm. We check for multicollinearity in the model with the variance inflation factor (VIF) test. As the independent variables n_{votes} and n_{cmt} in Model 1 have VIF value 1.020, which is well below 4. The VIF value obtained from Model 2 is also well below 4. Thus, the correlation between them is acceptable.

Table 4: Logistic regression results for H1a, H1b, H2a and H2b

Independent variables	Model 1 (Dependent variable: W_{cand}) Coeff.	SE	Model 2 (Dependent variable: W_{impl}) Coeff.	SE
Constant	-3.039***	0.071	-3.144***	0.075
Number of votes an idea had received (n_{votes})	0.002***	0.000	0.002***	0.000
Number of comments an idea had received (n_{cmt})	0.075***	0.005	0.038***	0.003

***: p-value <0.001

In order to test H2a and H2b, we continue using the logistic regression approach but replace the binary dependent variable W_{cand} with W_{impl} as H2a and H2b focus on idea implementation. We develop Model 2 by redefining $p = P(W_{\text{impl}} = 1)$ and employing it in Eq. 1. The VIF for the independent variables in Model 2 is 1.012, which is smaller than 4. Therefore, the correlation between the two independent variables is acceptable in Model 2. As shown in Table 3, both the number of votes (n_{votes}) and the number of comments (n_{cmt}) an idea had received are positively associated with the implementation measure (W_{impl}) at a significant level of $p < .001$. These findings support hypotheses H2a and H2b.

Previous studies in online user platforms suggest that the sentiment of user-generated ideas affect idea adoption and implementation (Chan et al., 2018). As discussed around H1c, H1d, H2c and H2d, we look at the sentiment of idea texts and comments to capture the factors which may also affect the consideration and implementation of posted ideas. The sentiment scores of idea texts and comments are calculated using the *sentiment()* function from the *sentimentr* package in *R*. For the sentiment scores of comments, because more than one comments are observed for most of the ideas, we calculate the average score of comments. As shown in Model 3 and 4 of Table 5, all the variables are significant. The relationship between the consideration and implementation of ideas, and the sentiment scores of idea texts and comments are positive. The results on the investigated independent variables (i.e., n_{votes} and n_{cmt}) are consistent with those in Table 4.

Table 5: Logistic regression results for H1c, H1d, H2c and H2d

Independent variables	Model 3 (Dependent variable: W_{cand}) Coeff.	SE	Model 4 (Dependent variable: W_{impl}) Coeff.	SE
Constant	-3.229***	0.072	-3.455***	0.081
Number of votes an idea had received (n_{votes})	0.004***	0.000	0.004***	0.000
Number of comments an idea had received (n_{cmt})	0.006***	0.000	0.006***	0.001
Sentiment score of idea	0.488**	0.214	0.509**	0.241
Average sentiment score of comments	3.409***	0.490	2.598***	0.593

***: p-value <0.001; **: p-value <0.01; *: p-value <0.05

As hypotheses H3a and H3b both involve continuous dependent variables, OLS models are considered. In particular, we use a hierarchical regression analysis approach which is able to capture both linear and non-linear relationship for the hypotheses. To validate H3a, three regression models are developed to test the relationship between the number of implemented ideas and contributed ideas. They are shown in Eqs. (2), (3) and (4) as follows:

$$n_{\text{ideas\_lead}} = \beta_0 + \beta_1 n_{\text{impl\_lead}} + \epsilon\,, \qquad (2)$$
$$n_{\text{ideas\_lead}} = \beta_0 + \beta_1 n_{\text{impl\_lead}} + \beta_2 n^2_{\text{impl\_lead}} + \epsilon\,, \qquad (3)$$
$$n_{\text{ideas\_lead}} = \beta_0 + \beta_1 n_{\text{impl\_lead}} + \beta_2 e^{n_{\text{impl\_lead}}} + \epsilon\,. \qquad (4)$$

Eq. (2) is the standard OLS model which aims to evaluate the linear relationship, whereas Eqs. (3) and (4) focus on non-linear relations. More specifically, Eq. (3) includes a quadratic term for the number of implemented ideas, i.e., $n^2_{\text{impl\_lead}}$ and Eq. (4) adds the exponential term $e^{n_{\text{impl\_lead}}}$. The validation results of the hierarchical regression analysis are presented in Table 6.

As shown in Model 5 of Table 6, the linear effect is positive (Coef.= 4.674) and significant. Next, we compare the three models to evaluate whether a non-linear relation exists. In Model 6, both the linear and quadratic effects are significant. The linear effect is positive, i.e., 8.963, and the quadratic term has a negative effect, i.e., -1.172. Moreover, the value of adjusted R-squared increases from 0.134 to 0.144. In Model 5, both the linear and exponential effects are significant. Similarly, the linear effect is positive, while the exponential effect is negative. The adjusted R-squared also increases but is less than the value in Model 6. Therefore, we can confirm the non-linear relationship between the number of contributed ideas and the number of implemented ideas. Given both Model 6 and 7 exhibit a concave curve, our results suggest that the slope becomes less positive (i.e., Coef. $= -1.172$ for the quadratic term) as the number of implemented ideas increases. Therefore, H3a is supported.

To test H3b, we use the hierarchical regression analysis approach again but focus on the number of comments contributed by lead users. The regression equations are shown in Eqs. (5), (6) and (7) and the analysis results are presented in Table 7.

$$n_{\text{cmt\_lead}} = \beta_0 + \beta_1 n_{\text{impl\_lead}} + \epsilon\,, \qquad (5)$$
$$n_{\text{cmt\_lead}} = \beta_0 + \beta_1 n_{\text{impl\_lead}} + \beta_2 n^2_{\text{impl\_lead}} + \epsilon\,, \qquad (6)$$
$$n_{\text{cmt\_lead}} = \beta_0 + \beta_1 n_{\text{impl\_lead}} + \beta_2 e^{n_{\text{impl\_lead}}} + \epsilon\,. \qquad (7)$$

Table 6: Hierarchical regression analysis on H3a

Model	Adjusted R-Squared	Sig. (ANONA)	Terms	Hierarchical Regression Coef.	SE	Sig.
Model 5: $n_{ideas\_lead} = \beta_0 + \beta_1 n_{impl\_lead} + \epsilon$	0.134	***	constant	7.197	0.210	***
			n_{impl_lead}	4.674	0.260	***
Model 6: $n_{ideas\_lead} = \beta_0 + \beta_1 n_{impl\_lead} + \beta_2 n^2_{impl\_lead} + \epsilon$	0.144	***	constant	6.803	0.212	***
			n_{impl_lead}	8.963	0.514	***
			$n^2_{impl\_lead}$	-1.172	0.122	***
Model 7: $n_{ideas\_lead} = \beta_0 + \beta_1 n_{impl\_lead} + \beta_2 e^{n_{impl\_lead}} + \epsilon$	0.140	***	constant	7.060	0.210	***
			n_{impl_lead}	5.555	0.285	***
			$e^{n_{impl\_lead}}$	-0.018	0.002	***

***: p-value <0.001; Dependent variable: number of ideas contributed by a lead user

Table 7: Hierarchical regression analysis on H3b

Model	Adjusted R-Squared	Sig. (ANONA)	Terms	Hierarchical Regression Coef.	SE	Sig.
Model 8: $n_{cmt\_lead} = \beta_0 + \beta_1 n_{impl\_lead} + \epsilon$	0.156	***	constant	4.620	0.197	***
			n_{impl_lead}	5.721	0.245	***
Model 9: $n_{cmt\_lead} = \beta_0 + \beta_1 n_{impl\_lead} + \beta_2 n^2_{impl\_lead} + \epsilon$	0.179	***	constant	4.046	0.199	***
			n_{impl_lead}	11.971	0.481	***
			$n^2_{impl\_lead}$	-1.707	0.114	***
Model 10: $n_{cmt\_lead} = \beta_0 + \beta_1 n_{impl\_lead} + \beta_2 e^{n_{impl\_lead}} + \epsilon$	0.169	***	constant	4.429	0.197	***
			n_{impl_lead}	6.957	0.268	***
			$e^{n_{impl\_lead}}$	-0.025	0.002	***

***: p-value <0.001; Dependent variable: number of comments contributed by a lead user

All three models confirm that the independent variable number of implemented ideas by a lead user ($n_{\text{impl\_lead}}$) has a significant positive effect on the user's commenting behaviour (p-value at the level of 0.001). Moreover, as the quadratic term (Coef.$= -1.707$ in Model 9) and the exponential term (Coef. $= -0.025$ in Model 10) of the number of implemented ideas are significant at the level of 0.001, non-linear relation is detected with the adjusted R-squared increases from 0.156 to 0.179 and 0.169. In particular, the linear effect is positive (i.e., 11.971), and the quadratic effect is negative (i.e., -1.707). This finding confirms H3b, suggesting the positive effect from the number of implemented ideas on the number of comments contributed by lead users decreases when the number of implemented ideas keeps increasing.

6. Discussion

Researchers argue that lead users are supplier of product ideas and peer-reviewers of ideas from other users (Hienerth & Lettl, 2017; Mahr & Lievens, 2012; von Hippel, 1986). However, little is known about what factors impact a high-tech firm's decision to independently consider and implement these ideas (Nambisan et al., 2018; Stanko et al., 2017). In this study, our empirical investigation of Microsoft PowerBI's platform disclosed two key factors of voting and commenting that are impacting the firm's decisions to consider and implement ideas Microsoft's lead users provide. In addition, we also examined whether lead users will contribute continuously on the platform if their ideas are implemented by Microsoft. From our analysis, we identify several interesting findings which contribute to the crowdsourcing, platform management and NPD literature.

First, we demonstrate that the popularity of an idea, measured by the number of votes it receives from other users on the platform, is likely to increase the probability for that idea being considered by the firm. Similarly, the more comments an idea receives, the more likely the firm will consider the idea for further development. These findings corroborate with previous studies, where researchers found that votes and comments received by an idea, were likely indicators on whether the firm will select an idea for further development (Hofstetter et al., 2018; Schemmann et al., 2016). However, our findings depart from these earlier studies on two points. Principally, these previous studies focused on ordinary users while we focus on lead users. As we presented in Table 1, lead users tend to possess more technical abilities, which explains the reason why popular ideas will be more likely to be considered by the firm. As these ideas have been self-selected by lead users on the platform as more likely to be technically feasible for development.

Moreover, our findings single-out that the number of comments an idea receives is a better indicator of whether the idea would be considered for development. An explanation for this is that evaluative comments provide the firm with more information and analysis about the suitability of an idea for development (Magnusson et al., 2016). Comments would include more tangible and explicit inputs that help the firm assess a given idea; whereas votes are merely an indicator of popularity. Although we discussed earlier that in a lead user community platform, reciprocal voting is less likely to happen; however, the positive and negative comments that an idea receives provide the firm with more information than merely votes. Hence, number of comments is a more useful indicator to aid the firm in its decision whether to consider an idea for further development.

Relatedly, we also demonstrate that popularity and comments that an idea receives are more likely to lead to the idea being implemented by the firm into its existing and new products. We have shown in Table 1 that previous studies found ideas generated by lead users were more likely to meet market needs due to lead user's advanced needs coupled with technical expertise (Herstatt et al., 2004; Nishikawa et al., 2013). However, as we discussed earlier, most studies tend not to measure the actual implementation of these ideas directly. Therefore, our findings extend the conclusions of these earlier studies, by showing the direct relationship between popularity and the number of comments in influencing a firm's implementation decision. Our findings also show that the amount of comments plays a more significant role in predicting a firm's implementation decision. An explanation for this is the stage-gate mechanism that most firms employ in their NPD process (Bayus, 2013; Cooper & Sommer, 2016). Ideas (i.e. externally- or internally generated) go through rigorous selection processes during NPD. Comments would contain more technical information about an idea that allows the firm to make implementation decisions when the idea is going through the many stages of NPD. Further findings show that when an idea is perceived as being negative or when it receives negative comments, the idea is less likely to be shortlisted and implemented by the firm. These findings highlight the importance for lead users to reconsider the framing of their ideas if they want to increase the likelihood of their ideas being picked up by the firm. Additionally, findings also reinforce the lead user theory's notion that lead users are excellent evaluators of ideas (Hienerth & Lettl, 2011; Magnusson et al., 2016), where we see the focal firm in our study trusting its lead users' assessment of an idea. Additionally, our results highlight the importance of sentiment as a predictor not just for idea development but also on the actual decisions that a firm makes during shortlisting and implementation.

We establish that there is a non-linear relationship between the number of ideas and comments supplied by lead users with the number of ideas being implemented by the firm. Hence, while our findings show positive relationship between these variables, this relationship exhibits a marginally decreasing trend. As we summarised in Table 1, previous studies found that lead users were mostly intrinsically motivated when it came to their willingness to participate in a firm's innovation activities (Frey et al., 2011; Jeppesen & Frederiksen, 2006). They were found to be motivated by the enjoyment of solving problems rather than purely economic benefit (Bogers et al., 2010; Shah, 2006). Therefore, we can explain this marginally decreasing relationship this way. Initially, when lead users see their ideas being implemented by the firm, they feel motivated to supply more ideas and provide more comments to evaluate other users' ideas. However, when more of their ideas are implemented by the firm, lead users feel less challenged by the problem-solving process and derive less enjoyment from it. Importantly, we extend earlier user community platform studies by drawing links between intrinsic motivation and lead users' participation in a firm's innovation activities. We do so by illuminating that implementing more ideas from lead users could potentially demotivate lead users from contributing further to the user community platform.

Contextually, having innovative suppliers is important for any firm wanting to achieve sustained competitive advantage. This is more so for high-tech firms as they operate in a highly turbulent environment. Prior studies found that innovative suppliers facilitated knowledge development within the firm, resulted in inter-firm organisational learning and increased supply chain agility (Hult et al., 2004; Kim & Chai, 2017; Köhler, Sofka, & Grimpe, 2012). Our findings show that firms can leverage lead users to complement their supply chain strategy. The user community platform acts as a conduit for the firm and lead users to share and develop innovation-related knowledge through iterative cycles of idea evaluation activities. Moreover, working with lead user ensures that NPD efforts are not only responding to the market, but shaping the highly complex and technologically diverse high-tech markets. Therefore, combining a firm's existing strategic sourcing activities with sourcing from user community platform contributes to more sustained supply chain advantage.

6.1 Theoretical and Practical Implications

Theoretically, we contribute to the user community platform literature by showing that an idea's popularity, the comments it receives and sentiment play an important role in predicting the likelihood these ideas will be shortlisted and implemented by the focal firm. Through our examination of quantity of votes and comments, idea sentiment, and comment sentiment, this study provides new evidence to understand idea popularity and sentiment's impact on firm's NPD decisions and the effects of these decisions on motivating lead users to contribute more inputs. Doing so, we extend prior studies' notion on idea popularity as a tool to evaluate ideas (Hienerth & Lettl, 2011; Hofstetter et al., 2018), by also showing the role of sentiment and popularity's direct impact on NPD. Relatedly, our findings also heed the call (Stanko et al., 2017) for more empirical insight into the direct effects of crowdsourcing tools on a firm's NPD activities.

Furthermore, this study's findings contribute to conversations around stimulating ideation in user communities (Frey et al., 2011; Han & Yang, 2019). The findings validate the direct effects of a firm's idea implementation decision on lead user's participation and ideation behaviour in a user community platform. Hence, this study is a step towards exploring other factors beyond the interactionist view that is commonplace in the literature. Additionally, our empirical findings also contribute to the growing literature emphasising the relative importance of innovative suppliers and knowledge sharing in building resilient supply-chains (Kim & Chai, 2017). In this study, we have established lead users in a user community platform can be a supplier of innovative solutions for high-tech firms. Our findings show that lead users' contributions, especially their evaluative comments, facilitate knowledge sharing amongst community users; which in turn, allows the firm to base NPD decisions on these comments.

Practically, this study demonstrates that firms wanting to crowdsource novel ideas through online lead user community platform need to focus on stimulating commenting behaviour and identifying incentives to motivate lead users. First, while it is extensively studied that an idea's popularity is an indication of its potential for development; our findings suggest otherwise. We suggest that the type of comments lead users provide to evaluate an idea and sentiment are more valuable to firms than popularity. User community platform is different from other forms of crowdsourcing method such as idea contest, in the way lead users interact with each other. In a user community platform, lead users are empowered to not only generate ideas but also to evaluate other users' ideas. Hence, firms operating user community platforms should put more emphasis on utilising sentiment analysis and analyse the content of evaluative comments that lead users provide as quality checks to guide idea sourcing decisions instead of relying solely on the popularity of an idea.

Second, incentivising lead users to continuously participate in a user community platform requires more than merely implementing the users' ideas. Although studies conclude that seeing their ideas being implemented afford a sense of accomplishment to lead users, thus spurring them to be more active. However, our findings demonstrate that users will lose motivation, as the firm implements more of their ideas. This somewhat paradoxical proposition means that a firm would need to provide other forms of incentive to motivate lead users to continuously supply much-needed ideas in the user community platform. Providing a combination of economic and intrinsic benefit could mitigate motivational issues that lead users face, which is vital as, without motivation, there would be a drop in participation (Amabile, 1998).

6.2 Limitations

Even though our findings make interesting contributions to literature, this paper has some limitations which could be avenues for future research. First, we have our focus on studying the role of lead users in the context of high-tech industries. Although it is widely considered that lead users play a crucial role in high-tech firms' product development, firms from more traditional industries can also source valuable ideas supplied by lead users in user community platforms. Thus, it is worth for future research to explore the role of lead users in diverse industries and the difference of lead users' behaviours in various types of user community platforms.

Second, we assumed that each set of hypotheses were independent from one another. The user community platform literature posits that not all submitted ideas will be considered by the firm. Among these shortlisted ideas, some will not be implemented. Thus, our analysis focused on exploring these group of hypotheses individually. Future studies could test for correlation between the hypotheses. For instance, to explore the probability for a shortlisted idea to be implemented by the firm.

Third, we employed a static approach to examine our research questions. While useful, a longitudinal or process research approach would shed more insight into the marginally decreasing trend impacting lead users' motivation to generate ideas and participate in peer-reviewing ideas actively. Future research could look at how this trend develops over time to pinpoint the exact number of ideas being implemented that tip the trend towards the diminishing end of the spectrum.

7. Conclusion

In this study, we have established positive relationships between an idea's popularity and sentiment, with a firm's decision to consider the idea for further development, and the actual implementation of the idea. Furthermore, we also demonstrated a marginally decreasing relationship between a lead user's propensity to generate new ideas and comments, with the number of the lead user's ideas being implemented by the firm. Consequently, the empirical study of Microsoft PowerBI's lead user platform reveals that sentiment and lead users' comments play a more important role in determining whether an idea will be shortlisted or implemented by the firm. Furthermore, lead users are only motivated up to a certain extent when their ideas are implemented. Hence, new ways are needed to keep them interested and motivated. These findings highlight the importance of understanding how to effectively shortlist ideas for consideration and implementation, and to benefit from sourcing product ideas through user community platforms.

References

Amabile, T. M. (1998). How to kill creativity. *Harvard Business Review, 76*(5), 76-87. Retrieved from http://link.gale.com/apps/doc/A21114520/AONE?u=learn&sid=zotero&xid=19ad00e4

Barnes, C. M., Hollenbeck, J. R., Jundt, D. K., DeRue, D. S., & Harmon, S. J. (2011). Mixing individual incentives and group incentives: best of both worlds or social dilemma? *Journal of Management, 37*(6), 1611-1635. doi:10.1177/0149206309360845

Bayus, B. L. (2013). Crowdsourcing new product ideas over time: An analysis of the dell ideastorm community. *Management Science, 59*(1), 226-244. doi:10.1287/mnsc.1120.1599

Bogers, M., Afuah, A., & Bastian, B. (2010). Users as innovators: a review, critique, and future research directions. *Journal of Management, 36*(4), 857-875. doi:10.1177/0149206309353944

Chatterji, A. K., & Fabrizio, K. R. (2014). Using users: When does external knowledge enhance corporate product innovation? *Strategic Management Journal, 35*(10), 1427-1445. doi:10.1002/smj.2168

Chen, Y., Pereira, I., & Patel, P. C. (2020). Decentralized governance of digital platforms. *Journal of Management*, 1-33. doi:10.1177/0149206320916755

Cooper, R. G., & Sommer, A. F. (2016). The agile–stage-gate hybrid model: a promising new approach and a new research opportunity. *Journal of Product Innovation Management, 33*(5), 513-526. doi:10.1111/jpim.12314

Coussement, K., Debaere, S., & Ruyck, T. D. (2017). Inferior member participation identification in innovation communities: the signaling role of linguistic style use. *Journal of Product Innovation Management, 34*(5), 565-579. doi:10.1111/jpim.12401

Di Gangi, P. M., & Wasko, M. (2009). Steal my idea! Organizational adoption of user innovations from a user innovation community: A case study of Dell IdeaStorm. *Decision Support Systems, 48*(1), 303-312. doi:10.1016/j.dss.2009.04.004

Ebner, W., Leimeister, J. M., & Krcmar, H. (2009). Community engineering for innovations: the ideas competition as a method to nurture a virtual community for innovations. *R&D Management, 39*(4), 342-356.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: what are they? *Strategic Management Journal, 21*, 1105-1121. doi:10.1002/1097-0266(200010/11)21:10/11<1105::aid-smj133>3.0.co;2-e

Felin, T., Lakhani, K. R., & Tushman, M. L. (2017). Firms, crowds, and innovation. *Strategic Organization, 15*(2), 119-140. doi:10.1177/1476127017706610
Felin, T., & Zenger, T. R. (2014). Closed or open innovation? Problem solving and the governance choice. *Research Policy, 43*(5), 914-925. doi:10.1016/j.respol.2013.09.006
Foss, N. J., Jeppesen, L. B., & Rullani, F. (2020). How context and attention shape behaviors in online communities: A modified garbage can model. *Industrial and Corporate Change*. doi:10.1093/icc/dtaa040
Frey, K., Lüthje, C., & Haag, S. (2011). Whom should firms attract to open innovation platforms? The role of knowledge diversity and motivation. *Long Range Planning, 44*(5-6), 397-420. doi:10.1016/j.lrp.2011.09.006
Füller, J. (2010). Refining virtual co-creation from a consumer perspective. *California Management Review, 52*(2), 98-122.
Füller, J., Hutter, K., & Faullant, R. (2011). Why co-creation experience matters? Creative experience and its impact on the quantity and quality of creative contributions. *R&D Management, 41*(3), 259-273.
Füller, J., Jawecki, G., & Mühlbacher, H. (2007). Innovation creation by online basketball communities. *Journal of Business Research, 60*(1), 60-71. doi:10.1016/j.jbusres.2006.09.019
Galton, F. (1907). Vox Populi. *Nature, 75*(1949), 450-451. doi:10.1038/075450a0
Gambardella, A., Raasch, C., & von Hippel, E. (2016). The user innovation paradigm: Impacts on markets and welfare. *Management Science, 63*(5), 1450-1468. doi:10.1287/mnsc.2015.2393
Gawer, A., & Cusumano, M. A. (2008). How companies become platform leaders. *MIT Sloan Management Review, 49*, 28-35.
Han, C. & Yang, M. (2019). Stimulating innovation on social product development: an analysis of social behaviors in online innovation communities. *IEEE Transactions on Engineering Management*. doi: 10.1109/TEM.2019.2955073.

Herstatt, C., Verworn, B., & Nagahira, A. (2004). Reducing project related uncertainty in the "fuzzy front end" of innovation: a comparison of German and Japanese product innovation projects. *International Journal of Product Development, 1*(1), 43-65. Retrieved from http://inderscience.metapress.com/content/LRW6LJLR11X4ND2H

http://inderscience.metapress.com/content/lrw6ljlr11x4nd2h/fulltext.pdf
Hienerth, C., & Lettl, C. (2011). Exploring how peer communities enable lead user innovations to become standard equipment in the industry: Community pull effects. *Journal of Product Innovation Management, 28*(s1), 175-195. doi:10.1111/j.1540-5885.2011.00869.x
Hienerth, C., & Lettl, C. (2017). Perspective: Understanding the nature and measurement of the lead user construct. *Journal of Product Innovation Management, 34*(1), 3-12. doi:https://doi.org/10.1111/jpim.12318
Hienerth, C., von Hippel, E., & Berg Jensen, M. (2014). User community vs. producer innovation development efficiency: A first empirical study. *Research Policy, 43*(1), 190-201. doi:10.1016/j.respol.2013.07.010
Hofstetter, R., Aryobsei, S., & Herrmann, A. (2018). Should you really produce what consumers like online? Empirical evidence for reciprocal voting in open innovation contests. *Journal of Product Innovation Management, 35*(2), 209-229. doi:10.1111/jpim.12382
Hult, G. T. M., Ketchen, D. J., & Slater, S. F. (2004). Information processing, knowledge development, and strategic supply chain performance. *Academy of Management Journal, 47*(2), 241-253. doi:10.2307/20159575
Jensen, R., & Szulanski, G. (2004). Stickiness and the Adaptation of Organizational Practices in Cross-Border Knowledge Transfers. *Journal of International Business Studies, 35*, 508-523. Retrieved from http://www.jstor.org/stable/3875236

Jeppesen, L. B., & Frederiksen, L. (2006). Why do users contribute to firm-hosted user communities? the case of computer-controlled music instruments. *Organization Science, 17*(1), 45-63. doi:10.1287/orsc.1050.0156

Kim, M., & Chai, S. (2017). The impact of supplier innovativeness, information sharing and strategic sourcing on improving supply chain agility: Global supply chain perspective. *International Journal of Production Economics, 187*, 42-52. doi:10.1016/j.ijpe.2017.02.007

Köhler, C., Sofka, W., & Grimpe, C. (2012). Selective search, sectoral patterns, and the impact on product innovation performance. *Research Policy, 41*(8), 1344-1356. doi:10.1016/j.respol.2012.03.020

Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal, 13*(S1), 111-125. doi:10.1002/smj.4250131009

Lettl, C., Herstatt, C., & Gemuenden, H. G. (2006). Users' contributions to radical innovation: evidence from four cases in the field of medical equipment technology. *R&D Management, 36*(3), 251-272. doi:10.1111/j.1467-9310.2006.00431.x

Lettl, C., Hienerth, C., & Gemuenden, H. G. (2008). Exploring how lead users develop radical innovation: opportunity recognition and exploitation in the field of medical equipment technology. *IEEE Transactions on Engineering Management, 55*(2), 219-233. doi:10.1109/TEM.2008.919717

Liebowitz, S. J., & Margolis, S. E. (1994). Network externality: An uncommon tragedy. *Journal of Economic Perspectives, 8*, 133-150. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=heh&AN=9407014388&site=ehost-live

Lüthje, C., & Herstatt, C. (2004). The Lead User method: an outline of empirical findings and issues for future research. *R&D Management, 34*(5), 553-568. doi:10.1111/j.1467-9310.2004.00362.x

Magnusson, P. R. (2009). Exploring the contributions of involving ordinary users in ideation of technology-based services. *Journal of Product Innovation Management, 26*(5), 578-593.

Magnusson, P. R., Wästlund, E., & Netz, J. (2016). Exploring users' appropriateness as a proxy for experts when screening new product/service ideas. *Journal of Product Innovation Management, 33*(1), 4-18. doi:10.1111/jpim.12251

Mahr, D., & Lievens, A. (2012). Virtual lead user communities: Drivers of knowledge creation for innovation. *Research Policy, 41*(1), 167-177. doi:10.1016/j.respol.2011.08.006

Nambisan, S., & Baron, R. A. (2009). Virtual customer environments: Testing a model of voluntary participation in value co-creation activities. *Journal of Product Innovation Management, 26*(4), 388-406.

Nambisan, S., Siegel, D., & Kenney, M. (2018). On open innovation, platforms, and entrepreneurship. *Strategic Entrepreneurship Journal, 12*(3), 354-368. doi:10.1002/sej.1300

Nishikawa, H., Schreier, M., & Ogawa, S. (2013). User-generated versus designer-generated products: A performance assessment at Muji. *International Journal of Research in Marketing, 30*(2), 160-167. doi:10.1016/j.ijresmar.2012.09.002

O'Leary, D. E. (2016). On the relationship between number of votes and sentiment in crowdsourcing ideas and comments for innovation: A case study of Canada's digital compass. *Decision Support Systems, 88*, 28-37. doi:10.1016/j.dss.2016.05.006

Ogawa, S. (1998). Does sticky information affect the locus of innovation? evidence from the japanese convenience-store industry. *Research Policy, 26*(7-8), 777-790. doi:10.1016/S0048-7333(97)00047-4

Ooi, Y. M., & Husted, K. (2016). Knowledge characteristics and organisational practices in user innovation. *Kindai Management Review, 4*, 22-39. Retrieved from https://www.kindai.ac.jp/rd/research-center/management-innovation/kindai-management-review/

Ooi, Y. M., & Husted, K. (2021). How traditional industries use capabilities and routines to tap users for product innovation. *Research-Technology Management, 64*(3), 31-42. doi:10.1080/08956308.2021.1891750

Parry, E., Farndale, E., Brewster, C., & Morley, M. J. (2021). Balancing rigour and relevance: The case for methodological pragmatism in conducting large-scale, multi-country and comparative management studies. *British Journal of Management, 32*(2), 273-282. doi:10.1111/1467-8551.12405

Podolny, J. M. (1994). Market uncertainty and the social character of economic exchange. *Administrative Science Quarterly, 39*(3), 458-483. doi:10.2307/2393299

Poetz, M. K., & Schreier, M. (2012). The value of crowdsourcing: can users really compete with professionals in generating new product ideas? *Journal of Product Innovation Management, 29*(2), 245-256. doi:10.1111/j.1540-5885.2011.00893.x

Schemmann, B., Herrmann, A. M., Chappin, M. M. H., & Heimeriks, G. J. (2016). Crowdsourcing ideas: Involving ordinary users in the ideation phase of new product development. *Research Policy, 45*(6), 1145-1154. doi:10.1016/j.respol.2016.02.003

Schuhmacher, M. C., & Kuester, S. (2012). Identification of lead user characteristics driving the quality of service innovation ideas. *Creativity and Innovation Management, 21*(4), 427-442. doi:10.1111/caim.12002

Schweitzer, F., Gassmann, O., & Rau, C. (2014). Lessons from ideation: where does user involvement lead us? *Creativity and Innovation Management, 23*(2), 155-167. doi:10.1111/caim.12058

Shah, S. K. (2006). Motivation, governance, and the viability of hybrid forms in open source software development. *Management Science, 52*(7), 1000-1014. doi:10.1287/mnsc.1060.0553

Stanko, M. A., Fisher, G. J., & Bogers, M. (2017). Under the wide umbrella of open Innovation. *Journal of Product Innovation Management, 34*(4), 543-558. doi:10.1111/jpim.12392

von Hippel, E. (1986). Lead users: a source of novel product concepts. *Management Science, 32*(7), 791-805. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=heh&AN=7023344&site=ehost-live

von Hippel, E. (1994). "Sticky information" and the locus of problem solving: implications for innovation. *Management Science, 40*(4), 429-439. Retrieved from http://www.jstor.org/stable/2632751

West, J., & Bogers, M. (2014). Leveraging external sources of innovation: a review of research on open innovation. *Journal of Product Innovation Management, 31*(4), 814-831. doi:10.1111/jpim.12125

Yang, M., & Han, C. (2019). Stimulating innovation: Managing peer interaction for idea generation on digital innovation platforms. *Journal of Business Research, 125*, 456-465. doi:10.1016/j.jbusres.2019.08.005