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Article

Lurkers versus Contributors: An Empirical Investigation of Knowledge Contribution Behavior in Open Innovation Communities

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Abstract: This study aims to examine and compare the mechanisms through which social learning processes influence the knowledge contribution behavior of lurkers and contributors in open innovation communities (OICs). Based on social learning theory and stimulus–organism–response (SOR) framework, this study developed a model of knowledge contribution formation mechanism from environmental stimuli (observational learning, reinforcement learning), organism cognition (self-efficacy, outcome expectancy) to behavioral response (initial contribution, continuous contribution). The model was tested using structural equation modeling based on a dataset collected through a questionnaire from an OIC of business intelligence and analytics software. The empirical results showed that, at the initial participation stage, observational learning had a significant effect on the organism's cognition of the lurkers, and indirectly influenced the initial knowledge contribution behavior through self-efficacy and outcome expectancy. At the continuous participation stage, observational learning had a significantly lower impact on the organism's cognition of contributors and only indirectly influenced continuous knowledge contribution behavior through outcome expectancy. In contrast, reinforcement learning influenced the organism's cognition of contributors and partially influenced their continuous knowledge contribution behavior through the mediating effects of self-efficacy and outcome expectancy. However, self-efficacy had a more pronounced effect on contributors' continuous knowledge contribution behavior than outcome expectancy. These findings provide practical guidance for the management of OICs to reduce knowledge contributor attrition and induce lurkers to evolve into knowledge contributors for sustainable community development.

Keywords: open innovation communities (OICs); stimulus–organism–response (SOR) theory; social learning theory; observational learning; reinforcement learning; knowledge contribution behavior

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1. Introduction

As technology advances, consumer preferences change and market competition intensifies, diverse knowledge is becoming an increasingly important part of a company's competitive advantage and long-term success. As a result, rather than exclusively relying on their internal research and development (R&D) capabilities and resources, today's companies are increasingly tapping into external knowledge and expertise by developing open innovation models. With the shift in innovation technology paradigms and the growth of Web 2.0 applications, open innovation communities (OICs) are increasingly being embraced by many companies as a means to augment their open innovation capabilities and generate a wealth of ideas and innovative products [1]. As such, an increasing number of companies are establishing OICs to gather knowledge and feedback from relevant stakeholders. For example, companies are building OICs, such as IBM's crowdsourcing community, to gain employee knowledge of corporate policies and other issues [2,3], and to obtain incubator business ideas from their employees and other stakeholders. On the consumer side, branded communities enable companies to obtain customer preferences and ideas for new products or services [4,5]. For example, Microsoft's Power BI community collects customer intelligence and knowledge contributions to improve business intelligence and analytics products and solutions. In OICs, heterogeneous knowledge bases can be bundled and accessed by different stakeholders, leading to the development of new products, processes, or business models [1,6].

While empowering the respective stakeholders, i.e., employees, customers, and citizens, the issue of promoting participation and knowledge contribution in open innovation has been a prominent and recurring issue in open innovation research and practice [7,8]. Yet, previous studies have mostly examined contributor behavior (e.g., [9,10]), while less attention has been paid to lurkers, i.e., members who only read and observe without actively contributing to online communities and platforms [11]. While encouraging contributor engagement is crucial, stimulating lurker participation in OICs (e.g., idea crowdsourcing communities and virtual communities of practice) is equally important for at least three reasons. First, a key objective of OICs is to facilitate the incorporation of feedback and ideas from a wider range of members [12]. Soliciting input from lurkers can broaden the scope and extent of contributions. Second, lurkers typically represent a large percentage of participants in OICs, e.g., up to 90% [13]. Thus, they represent a broad range of potential contributors from whom ideas and feedback can be obtained. Third, converting lurkers into contributors can compensate for the loss of contributors that typically occurs in OICs. In practice, the phenomenon of losing a large number of active users has led to the gradual decline of many OICs [14]. Low willingness of users to continue participating and high member attrition rates have been reported as prominent problems. For example, in their study of OICs, Vershinina, Phillips [5] estimated that the average monthly contributor attrition rate exceeded 50%. Therefore, promoting user knowledge contribution and community engagement to reduce active user attrition has attracted a lot of research in the field of open innovation and knowledge management.

The extant research on open innovation has explored the motivations of user knowledge contributions from several theoretical perspectives. For example, based on social capital theory, Shi [15] demonstrated the impact of perceived certification and performance expectations on the initial knowledge contributions of community members. Moser and Deichmann [16] showed that trust, reciprocity norms, knowledge self-efficacy, perceived relative advantage, and perceived usefulness have significant effects on continuous user knowledge sharing. Orelj and Torfason [17] showed that identity trust, self-efficacy, personal outcome expectation and community-related outcome expectation have a significant effect on user knowledge contribution. Fang, Li [18] demonstrated that social interaction and satisfaction have a positive impact on continuous user participation. Based on the value theory perspective, Cheng, Gu [19] argue that reciprocity is an important driver of knowledge contribution by lurkers. Cai and Shi [20] argued that perceived usefulness, social influence, and perceived information infrastructure have a positive impact on sustained information sharing behavior. Fayn, des Garets [21] explored the motivations of different users for sustained participation by dividing community users into lurkers, questioners, and answerers based on the theory of planned behavior. Bui and Jeng [22] divided community users into lurkers and contributors and analyzed the differences in motivation for knowledge contribution among them.

While understanding of what motivates lurkers to contribute remains limited, the knowledge gap is even more pronounced for studies comparing contributors and lurkers [23]. When examining this issue in previous studies, several research gaps in the literature remain prominent:

- First, previous studies e.g., [24,25] have confirmed the significant influence of intrinsic cognitive factors, such as self-efficacy and outcome expectancy, on user knowledge-contributing behavior or intentions. Previous studies have also investigated the indirect effects of external environmental factors such as social interactions, social influence, reciprocity, and trust on continuous contribution through intrinsic cognitions and attitudes. However, the path analysis from external environment to intrinsic cognition to knowledge contribution behavior in previous studies has insufficient explanatory power for external stimuli in the specific knowledge exchange context of OICs. In addition, they lack specific exploration of community peer influence and social learning effects.

- Second, at the same time, the initial contribution of lurkers and the continuous contribution behavior of contributors are not clearly distinguished to explain the differences in the influence mechanisms and motivations of user knowledge contributions under different stages. Such a comparative study could provide a more comprehensive strategy for sustaining OICs and maximizing the benefits gained from open innovation projects.
- Third, prior research on online participation has investigated other contexts of online platforms such as knowledge sharing [26], open source software (OSS) development [27], and social support [28]. Since OICs are not monolithic, there may be both similarities and differences in the dynamics of participation in OICs compared to other platforms. Similar to other networking platforms, participation in OICs (i.e., contributing ideas and raising issues to be addressed) is a collective action in which members voluntarily contribute their experiences, perspectives, and knowledge, even if they do not know each other [29]. As a result, their participation leads to the creation of innovative products and services that are useful to all stakeholders, including those who do not contribute.

The aforementioned practical and theoretical challenges inspired this study to examine the motivational factors of knowledge contribution behavior of contributors and lurkers in OICs from the perspective of social learning theory. In particular, this study draws on social learning theory [30] and stimulus–organism–response (SOR) framework [31] to model the formation mechanisms of knowledge contribution behavior in OICs from environmental stimulus (observational learning, reinforcement learning), organism cognition (self-efficacy, outcome expectancy) to behavioral response (initial contribution, continuous contribution). The model was empirically validated with a survey of contributors and lurkers based on a questionnaire dataset collected from the Microsoft Power BI community (https://community.powerbi.com/, accessed on 8 October 2022). The results revealed significant differences in the antecedents of participation between the two groups, as hypothesized. Specifically, at the initial participation stage, observational learning had a significant effect on organism cognition of lurkers, and indirectly influenced initial knowledge contribution behavior of lurkers through self-efficacy and outcome expectancy. At the continuous participation stage, observational learning had a significant effect on the organism cognition of contributors, while only indirectly influencing continuous knowledge contribution behavior through outcome expectancy.

The findings from this study provide valuable insights for understanding and promoting the different participation strategies of contributors and lurkers in OICs. The main contributions of this study to the literature on open innovation can be summarized as follows:

- This study provides an empirical understanding of, and new insights into, the mechanisms through which two social learning processes, observational learning and reinforcement learning, influence the knowledge contribution behavior of lurkers and contributors in OICs during the initial and continuous participation phases.
- This study provides a theoretically grounded explanation and offers a new perspective on the underlying nature of lurkers in OICs, which is less understood than contributors in the existing literature [9,32]. By understanding lurkers as observers with similar psychological scaffolding, this study finds that lurkers can gain self-efficacy and motivation to learn by observing the successful contributions of other users in the community.
- From a practical perspective, this study provides practical guidance for the management and operation of OICs to minimize the attrition rate of knowledge contributors and induce lurkers to evolve into sustainable community development and growth.

The rest of the paper is organized as follows. Section 2 provides a literature review of the key conceptual and theoretical background. Section 3 discusses the development of the research model and hypotheses. Section 4 describes the research methodology, including the constructs used in the study, related measures, and data collection procedures. Section 5 presents the data analysis and results of the study. Section 6 discusses the results of this study and their implications for research and practice. Section 7 discusses the limitations of this study. Finally, Section 8 provides the overall conclusions of this study.

2. Literature Review and Theoretical Background

2.1. Knowledge Contribution in Open Innovation Communities

Since its introduction by Chesbrough [33], the open innovation paradigm has attracted significant interest as an important source of knowledge and intelligence that endows firms with competitiveness and innovativeness. In the open innovation paradigm, firms can and should leverage external and internal ideas, as well as purposeful knowledge inflow and outflow to accelerate and streamline the innovation process, making it more efficient and effective. According to Chesbrough [34], the inflow of knowledge involves the use of existing ideas and expertise outside the boundaries of the firm. Thus, knowledge itself may not be a company's most valuable asset, but rather the way it is used effectively in the innovation process and shared with stakeholders [35,36]. The development of innovation is therefore cyclical and underpinned by knowledge sharing and stakeholder participation in OICs. Meanwhile, knowledge contribution and knowledge search are different types of knowledge behavior that are closely related and jointly contribute to knowledge sharing [37]. In OICs, users usually act as knowledge supply and knowledge demand subjects [38]. The activities of knowledge contributors constitute a holistic view of various knowledge behaviors, including knowledge providers who contribute or share knowledge [39], knowledge seekers [40,41], and knowledge consumers [42]. Drawing on previous research and analysis of the connotations of knowledge contribution behavior, users of OICs can be viewed from three perspectives: knowledge provision, knowledge seeking, and bidirectional knowledge behavior, as shown in Table 1.

Table 1. Classification of users and types of knowledge contribution behavior in OICs.

Classification of Users Based on Knowledge Behavior	Type of Knowledge Contribution Behavior	Source
Knowledge supply	Knowledge Sharing	[9,16,43]
	Knowledge Contribution	[4,19,44]
	Knowledge Supply	[8]
	Knowledge Gathering	[22]
	Knowledge Creation	
Knowledge demand	Knowledge Search	[20]
	Knowledge Assessment	[18]
	Knowledge Filtering	[45]
	Knowledge Adoption	[9]
	Knowledge Utilization	[10]
	Knowledge Reuse	[46]
Bidirectional behavior	Knowledge Exchange	[15,40,47]
	Knowledge Transformation	[4,11]
	Knowledge Transfer	[22,38]

From the perspective of knowledge supply, previous studies have mainly investigated the antecedents and consequences that influence user knowledge contribution or knowledge sharing from the perspectives of internal and external motivation, social capital, social cognition, and organizational climate. For example, Liu, Yang [48] applied collective action theory to verify the effects of individual motivation and social capital on knowledge contribution and found that structural capital had the most significant effect on knowledge sharing in OICs. Prom Tep, Aljukhadar [41] applied social exchange theory to explore knowledge contribution behavior and found that knowledge self-efficacy and usefulness had significant effects on knowledge contribution. Johansson, Islind [37] integrated social capital and social cognitive theories to verify the effects of social interaction, trust, reciprocity, identity, and outcome expectancy on knowledge sharing intention. Based on social cognitive theory, Zhao and Detlor [49] divided the factors affecting knowledge sharing into two categories, personal factors including self-efficacy and outcome expectations, and environmental factors including multidimensional trust. Ma, Lu [50] showed that technical designs such as rating systems and user presentations can drive knowledge contributions.

From the perspective of knowledge demand, previous studies applied the dual process theory of information processing to explain the knowledge adoption behavior of community members, adding type consistency and information consistency cues to heuristic cues and exhaustive possibilities [19,20]. Sun, Zhang [4] used a case study to divide the innovative knowledge reuse process into six stages, including redefining the problem and methods, searching, and evaluating other reusable ideas, and continuing the development of selected ideas. In investigating user motivations for knowledge search, Vershinina, Phillips [5] found that the main purpose of users searching from a knowledge base is to solve problems. Pirkkalainen, Pawlowski [40] studied knowledge reuse within the open design community and proposed a third type of reuse, different from replicative and innovative reuse, called custom reuse.

From an integrated perspective of bidirectional knowledge behavior, Bui and Jeng [22] explored the factors influencing knowledge contribution, knowledge acquisition, and reuse behavior in an organizational context and their association analysis. They found that for the reciprocal motivation, user knowledge acquisition and reuse behavior stimulate user knowledge contribution intention. Moreover, as the amount of knowledge contribution increases, users evolve from continuous knowledge seekers to continuous knowledge contributors [20]. Conversely, in another study, user contribution behavior actively promotes knowledge acquisition, which plays a crucial role in community outreach [16]. Luo, Lan [10] studied the knowledge sharing and knowledge seeking behavior of online community of practice members based on social capital theory and interactive memory systems and examined the impact of social networks on knowledge exchange. Orelj and Torfason [17] studied knowledge transfer between different development groups in open-source communities and found that knowledge transfer within dense groups had a positive impact on knowledge transfer between sparse groups.

Much of the previous research on open innovation has focused on the use of readily available external knowledge. However, the way this knowledge is created in the first place has often been overlooked. The development of open innovation is inextricably linked to the sustainability of participation, and the loss of many active users has led to the gradual decline of many communities in practice. The low willingness of users to continue participating and the high rate of membership attrition are problems that are prominent in the context of open innovation. Moreover, the failure of a large number of existing open innovation projects is due to the low willingness of community stakeholders to use formal knowledge contribution models, preferring informal networks of interaction and participation [23]. According to Wang, Zhang [11], very little new knowledge is learned through formal organizational training, and the vast majority is learned through informal learning interactions and observations [17].

Learning is fundamentally a social process, and OICs constitute an efficient and informal social learning system [42,51,52]. Typically, in the context of OICs, tacit knowledge is embedded in individual skills, wisdom, and experience, which is difficult to reveal and can only be effectively shared through social interaction and informal learning processes [8]. Therefore, to improve competitiveness and innovation efficiency, companies must pay attention to the development of learning capabilities of community members, especially informal learning capabilities. In this regard, exploring the knowledge formation mechanisms of community users and understanding their knowledge contribution behavior are of great relevance to improve user knowledge contributions and informal learning in OICs. In addition, promoting user knowledge contribution and community participation and reducing the loss of active users are topics of great interest to practitioners and researchers alike.

2.2. Contributors versus Lurkers

Among the limited studies comparing contributors and lurkers in OICs (see Table 2, which also describes how this study compares to previous studies), earlier studies focused on understanding differences in their actual behavior rather than motivational factors in their knowledge formation and learning mechanisms [38,49,53]. Findings from previous studies [26,52] suggested that lurkers were less enthusiastic about seeking knowledge from others and gaining full membership in the OIC than contributors. This finding was subsequently confirmed in study by Nguyen, Malik [47].

Table 2. Sample of previous studies comparing contributors and lurkers in virtual communities.

Study	Context	Nature of Study	Major Findings	Comparison with Our Work
Orelj and Torfason [17]	Virtual communities	Conceptual	• For lurkers to participate, they must have a strong desire to align with their goals, plans, values, beliefs, and interests. • If a community member believes that the lurker is credible and that changing their beliefs would be consistent with their goals, then they can convince the lurker to change their views.	• Our study elucidates unique motivational antecedents (observational learning, reinforcement learning, self-efficacy, and outcome expectations) that are important for OIC participation. • In contrast to Orelj and Torfason [17], who address these questions conceptually, our study presents empirical evidence of what drives contributor and lurker participation.
Kim, Salvacion [36]	Virtual communities	Field experiment	• Lurkers support a more diverse and less popular selection of material than contributors, and they are more likely to promote something from their network. • Visitors who used the honeybee method to promote material were twice as likely to submit new content to the site in the next month.	• Based on social learning theory and the SOR model, our work develops and tests a comprehensive set of antecedents of participation for contributors and lurkers. • In addition, our comparative model provides a more comprehensive and theoretically grounded (construct hierarchy theory) understanding of the differences in factors that influence contributor and latent participation.
Smirnova, Reitzig [54]	Open-source software platforms	Survey of 471 community members (280 contributors and 191 lurkers)	• Lurkers are influenced by normative influences (as measured by admiration for the contributor). • Admiration and normative influence motivate contributors.	• Rather than assessing differences in factors affecting contributor and lurker participation a posteriori, as in this study, i.e., in the data analysis, our work predicts them a priori using framing level theory. In addition, our study models and tests the effects of a broader set of incentive variables.

Table 2. *Cont.*

Study	Context	Nature of Study	Major Findings	Comparison with Our Work
Le, McConney [32]	Social networking sites	Mixed method approach including focus-group interviews, and 393 respondents to an online survey, of which 219 were lurkers	• Contributors have more motivation than lurkers to join an online community that requires outreach to the community and/or engagement with other members. • Lurkers were less satisfied with their online community experience and less enthusiastic about community involvement than contributors.	• The purpose of this study was to provide a preliminary understanding of the differences between contributors and lurkers. No assumptions were made and differences between the two groups were assessed by chi-square tests. • Our study adds to the body of knowledge by providing a theory-driven and empirically confirmed explanation of the motivations of contributors and lurkers to participate in OICs.
Nguyen, Malik [47]	Online communities revolving around personal interests, health concerns, geography, and occupations	Survey of 518 members from 20 asynchronous online communities	• There were significant differences in the interests of lurkers and contributors in terms of information seeking and confidence in the competence and goodwill/integrity of other members. • Lurkers have less confidence in the competence and goodwill/integrity of others than do contributors.	• This study investigates changes between contributors and lurkers in terms of trust, willingness to provide and receive knowledge, and the desire to exchange social support. • Our study extends the analysis of the distinction between contributors and lurkers to a different setting, namely OICs, and provides a comprehensive collection of the antecedents of participation from which relevant hypotheses emerge. • We test these hypotheses using structural equation modeling.

According to the few studies that have investigated lurker motivation, once lurkers begin to participate, their motivation may become positive and enthusiastic [26]. In an analysis of contributor and lurker motivations, Yang, Li [26] found that, compared to contributors, lurkers were motivated by enjoyment and normative influence rather than usefulness and status benefits. Their study extends our understanding of lurkers and contributors with respect to several motivational factors (status, enjoyment, and normative influence). However, other motivational factors of user participation, such as social learning mechanisms and outcome expectations [55], may be applicable to OICs and were not sufficiently considered in previous research. Previous studies have also identified several motivational factors, such as self-efficacy and empowerment, that may also influence individual contributions at different stages of participation in OICs. A study by Kim, Lee [31] concluded that having relevant skills and resources can influence individual decisions to participate in online communities. This argument was supported by the authors of [32], who proposed a conceptual framework to explain the online participation decisions of contributors and lurkers. According to this framework, lurkers prefer not to participate because they lack the necessary competencies (e.g., self-efficacy) as well as the desire to participate. However, this framework has not been empirically tested, and the distinction between lurkers and contributors is inferred from earlier research findings without a specific theoretical basis. At the same time, the initial contribution of lurkers and the continuous contribution behavior of contributors are not clearly distinguished to explain the differences in user learning processes and motivations at different stages of participation and knowledge contribution. To contribute to this recurrent and important issue, this study aims to develop a theoretically grounded antecedent model of contributor and lurker participation, and evaluate the model through a field survey. The underlying theoretical background of this model is now explained.

2.3. Social Learning Theory

According to Wenger [30], learning is fundamentally a social process characterized by a rational, peripheral process of individual involvement in a specialized domain. The shift from individual perceptions of learning to a focus on learning contexts can be traced back to Bandura's social learning theory [56]. This theory views learning as a cognitive process that produces responses to social contextual stimuli and explains the mechanisms of the way humans shape and influence their behavior through social learning. It also provides useful insights into the associations between the environment as a prerequisite for behavior, interaction determinism, self-efficacy, and outcomes as secondary determinants of behavior. Social learning theory is concerned with learning that occurs in social settings and the way people learn from each other [57]. Wenger-Trayner, Wenger-Trayner [58] further described socialization in learning and proposed a conceptual analytical framework to understand social learning systems. According to their framework, there are three core concepts of social learning systems: learning communities, community boundaries, and user identities. Community boundaries constitute an important construct of social learning systems, which provide learning opportunities that are different from the community context. Typically, in OICs, community boundaries are dynamic and boundary learning maximizes individual benefits [59]. User identity is another core concept of social learning theory in OICs. The formation of identity is an important part of learning. Identity has social attributes (how others perceive you) and personal attributes (how you perceive yourself) [60].

In social learning systems, people can acquire new standards of behavior through direct experience or by imitating or observing the behavior of others [57]. There are two types of learning in the social learning process: observational learning (OL), also known as indirect experiential learning, in which individuals learn by observing the behavior of others and their outcomes, and reinforcement learning (RL), also known as direct experiential learning, in which individuals learn from the positive and negative outcomes of their own previous behavior [60,61]. Social learning involves deepening the mutual commitment of members through participation in social activities. In the context of OICs, social learning is based on collaboration and is a part of community learning; however, not all community learning involves social learning [62]. Social learning in OICs is stage-based, where learning is seen as a trajectory into the community, emphasizing the importance of social engagement in shaping member identities, with significant shifts in knowledge and skills bringing about corresponding shifts in identity and motivation [1].

Since social learning theory is concerned with learning that occurs in social settings and the way people learn from each other, social learning is an important perspective for understanding knowledge contribution behavior and differences in activities between lurkers and contributors in OICs [47,55]. A key facet of OICs is to facilitate the generation and dissemination of tacit knowledge. Exchanging tacit knowledge through OICs can foster better idea generation and reduce learning time for new members. According to Panda and Mohapatra [14], OICs are an ideal learning tool that serves a number of purposes, such as sharing domain perspectives, trust, long-term relationships, mutual recognition, and creating practical activities. In recent years, OICs have been widely used in several professional fields, especially in education, public health, and technological advancement. The use of OICs can strengthen interdisciplinary innovation and learning and can enable members to integrate multidisciplinary perspectives for collaborative innovation and learning [4,14,54]. However, Wang, Zhang [51], in evaluating the effectiveness of users in OICs, found that most community users remain engaged in only browsing activities and less in content contribution and knowledge sharing. The interaction dynamics and motivational factors surrounding knowledge contribution such as self-efficacy, outcome expectations, and how to increase member engagement through activity design and content creation, are key issues that need to be addressed.

2.4. Stimulus–Organism–Response (SOR) Framework

The stimulus–organism–response (SOR) framework [63] provides a systematic view of the way individual cognitive responses to environmental stimuli influence their subsequent behavioral decisions. In the SOR framework, the stimulus (S) represents the motivational forces from external environment. The external stimulus S influences the internal state of the organism O, which in turn drives the subsequent individual behavioral response R. The organism part of the SOR framework emphasizes the intermediate interaction process between the external environmental stimulus and the individual behavioral response [64]; it refers to the internal state of the individual, i.e., the cognitive and affective response. The active behavior exhibited by individuals, i.e., user contribution behavior, are usually more likely to be directly influenced by their own cognition. Cognitive responses represent the mental processes by which an individual's brain acquires, retains, retrieves, and processes information. Affective responses represent the emotions that individuals exhibit in response to environmental stimuli such as excitement, empathy, and pleasure. After an individual receives environmental stimuli, they are transformed into meaningful information to influence their subsequent behavioral responses [65].

In the context of OICs, the proactive behavior exhibited by individuals, i.e., knowledge contribution behavior, is usually more directly influenced by their own perceptions, experiences, and opinions. When individuals first join an OIC, they usually have some explicitly targeted need to interact with others in the community from which they can obtain product information support from the community or from other users. This online social support can be seen as an external stimulus. Then, individuals receive online information support and online emotional support from the community and develop some cognitive and emotional responses in the user community, i.e., a sense of self-belonging and self-efficacy; subsequently, they develop a series of behavioral responses that benefit the online user community, which are expressed as knowledge contribution behavior.

According to the SOR framework, the social learning process of individuals in a community involves three main components: external stimulus, organism, and response, indicating that individual internal cognitive and affective states change after being stimulated by external environmental factors, resulting in behavioral responses. According to social learning theory [58], an individual's peer behavior and past behavior and their outcomes constitute the environmental factors to which the individual is exposed, and the individual becomes familiar with and adapts to the external environment through direct and indirect participation. Thus, social learning processes involve the adaptation of individual psychological or behavioral responses after experiencing stimuli from environmental factors. This argument motivates the present study to integrate the theoretical perspectives of social learning and SOR to develop a model to investigate and compare the mechanisms by which the two social learning processes, observational learning and reinforcement learning, influence the knowledge contribution behavior of lurkers and contributors in OICs at the initial and continuous participation stages.

3. Research Model and Hypotheses

Based on social learning theory and the SOR framework, two learning styles, observational learning (OL) and reinforcement learning (RL), were selected as external environmental factors in the S part of the proposed model. Self-efficacy (SE) and outcome expectancy (OE), which are important social cognitive factors for individuals, were included in the O part. Individual social cognition mediates environmental stimuli, which in turn influence initial knowledge contribution behavior (IKC) and continuous knowledge contribution behavior (CKC), thus constituting individual behavioral responses in the R part of the model, as shown in Figure 1.

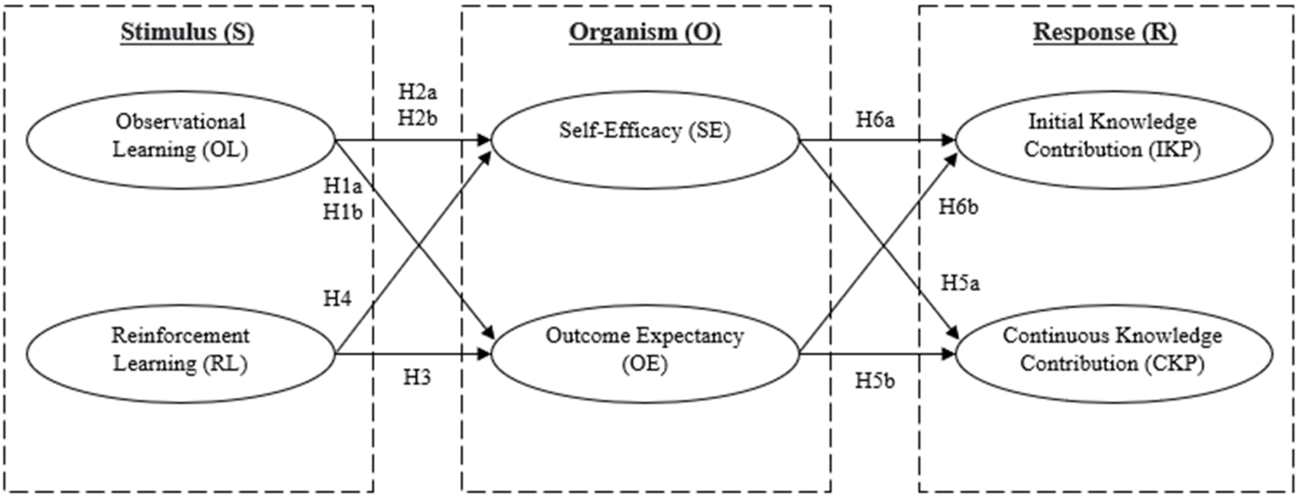

Figure 1. Social learning-based user knowledge contribution model in OICs.

3.1. Observational Learning and Outcome Expectancy

Outcome expectancy (OE) is a cognitive consideration inherent to learners in the social learning process. It refers to an individual judgment of the likely outcome of a behavior before it occurs [66]. According to social learning theory, by observing the outcomes produced by the behavior of others, individuals can grasp the results that can be obtained by performing the behavior in a given context. If an individual observes positive reinforcement of another person's behavior, they can stimulate their own outcome expectations and can perceive the same rewarding nature of performing a specific behavior [17]. In OICs, users do not participate in the process of knowledge contribution as isolated individual behavior, but as a social process through learning from the behavior of other users and their outcomes, as well as their own previous behavior and outcomes. Users can observe or imitate the behavior of other users, reassess their perceptions, and influence their outcome expectations [18]. During their knowledge contributions, community users can easily observe knowledge posts contributed by other users. If, after observing others' knowledge contributions, negative outcomes such as punishment and ignorance are observed, then learners will negatively influence the behavior and lower their outcome expectations of the behavior so that they do not repeat it. Similarly, if positive outcomes, such as rewards and engagement, are obtained after observing others' knowledge contributions, then there will be a positive impact on the behavior, thus increasing the outcome expectation of the user knowledge contributions. Based on the above theoretical analysis, the following hypotheses are proposed in this study:

H1a. *Observational learning has a positive impact on the outcome expectancy of the initial knowledge contribution of lurkers.*

H1b. *Observational learning has a positive impact on the outcome expectation of continuous knowledge contribution of contributors.*

3.2. Observational Learning and Self-Efficacy

Self-efficacy (SE) is another form of internal cognition experienced by learners during the social learning process. It refers to an individual's beliefs about their ability to perform a behavior; therefore, it represents an important factor that influences an individual's behavior [67]. Observing the behavior of others can increase learner awareness of their ability to successfully perform that behavior [17]. In the context of OIC, users can improve their knowledge by observing knowledge posts in the community and learning from the knowledge contributed by other users [32]. It was found that people with higher expertise, skills and abilities are more likely to provide useful content in online forums and also induce a higher sense of self-efficacy [36]. Similarly, users with a certain level of knowledge tend to feel capable of contributing knowledge within the community. Furthermore, by observing the knowledge contributed by others in the community, users indirectly gain confidence in contributing knowledge in the community by acquiring the rules of how the community operates, the characteristics of the community, and the skills required for community participation. Thus, users develop a form of vicarious learning by observing the participation behavior of other users and their outcomes. This experience of indirect vicarious learning also allows users to gain domain-specific expertise and skills, thereby increasing their self-efficacy. Based on the above theoretical analysis, the following hypotheses are proposed in this study:

H2a. *Observational learning has a positive impact on the self-efficacy of knowledge contribution of lurkers.*

H2b. *Observational learning has a positive impact on self-efficacy of knowledge contribution of contributors.*

3.3. Reinforcement Learning and Outcome Expectancy

Reinforcement learning (RL) occurs when an individual observes the consequences of a prior behavior and changes their behavior based on the consequences of that behavior [68]. When positive feedback is received for the previous behavior, then the individual continues to engage in that behavior. This suggests that community users who have contributed knowledge will reinforce learning through the consequences of previous behavior. Research has shown that the consequences of previous behavior lead community users to form expectations that produce similar outcomes in future settings [8,20,59]. Le, McConney [32] also confirmed that performance results obtained from previous behavior can significantly affect individual outcome expectancy. In the case of OIC, if users perceive that their past knowledge contributions have obtained positive and favorable outcomes, this may increase user outcome expectancy. Conversely, if user knowledge contributions have obtained negative outcomes such as penalties, then users will lower outcome expectancy. Based on the above theoretical analysis, the following hypothesis is formulated for this study:

H3. *Reinforcement learning has a positive impact on the outcome expectancy of contributors to continue contributing knowledge.*

3.4. Reinforcement Learning and Self-Efficacy

The user's success in performing the behavior provides the most powerful source of information about the user's self-efficacy. That is, successes in previous behavior increase self-efficacy, while experienced failures may decrease self-efficacy, which in turn supports users in deciding whether to reinforce or reduce the behavior [69]. Moise and Anton [70] argued that sharing knowledge with others increases user self-efficacy. Smirnova, Reitzig [54] also found that by sharing useful knowledge with others in an online community, participants would gain more confidence in their achievements. Therefore, in OIC, users make judgments based on the results of their previous knowledge contribution behavior and believe that the success or failure of the behavior affects self-efficacy. Based on the above theoretical analysis, the following hypothesis is proposed in this study:

H4. *Reinforcement learning has a positive impact on the self-efficacy of contributors to continue contributing knowledge.*

3.5. Self-Efficacy, Outcome Expectancy and Knowledge Contribution

Previous studies have shown that the users' recognized participation in OIC significantly increases their performance and engagement, which further promotes knowledge contribution behavior [9,31,48]. Panda and Mohapatra [14] concluded that outcome expectancy has a significant positive impact on user knowledge sharing behavior. When community users expect to gain from knowledge contribution, then they will engage in knowledge contribution behavior. Kim and Son [71] showed that self-efficacy for knowledge contribution significantly influences lurker willingness to contribute knowledge. Chapman and Dilmperi [23] confirmed that knowledge self-efficacy is an important motivation for posters to contribute knowledge. Kaplan Mintz, Arazy [57] also found that self-efficacy has a significant effect on the users' continued participation in OICs. In line with previous studies, the present study posits that users are likely to participate in the community when they believe they are capable of contributing knowledge. Building on this foundation, the following hypotheses are proposed in this study:

H5a. *Outcome expectancy has a positive impact on the initial knowledge contribution behavior of lurkers.*

H5b. *Outcome expectancy has a positive impact on the continuous knowledge contribution behavior of contributors.*

H6a. *Self-efficacy has a positive impact on the initial knowledge contribution behavior of lurkers.*

H6b. *Self-efficacy has a positive impact on the continuous knowledge contribution behavior of contributors.*

4. Research Methodology

To test the research model and hypotheses, this study followed a quantitative research approach, comprising a self-administered questionnaire to collect data and structural equation modeling (SEM) to analyze the data. This section discusses the research steps, including instrument development, data collection, and data analysis.

4.1. Measures Development

To ensure the content validity of the measurement items, the questionnaire used well-established measures from previous studies and adapted to suit the objectives and context of the study. The observational learning (OL) measurement items were derived from Kwon, Shin [72] in the context of professional communities, and they were based on the finding that people learn by observing the behavior and outcomes of others [72]. According to their findings, user knowledge sharing behavior in OICs is mostly in the form of posting and reposting, implying that user observational learning in communities primarily takes the form of informative behavior such as knowledge searching, browsing, and viewing. The measurement items for reinforcement learning (RL) were adapted from Cheung, Liu [73], who refer to reinforcement learning through user feedback obtained following previous user knowledge contributions. To develop items to measure reinforcement learning, this study draws on earlier user feedback research, including the user intrusion dimension of online interactions and the affective dimension of social support [74,75]. The self-efficacy (SE) items were adapted from Luo, Lan [10]. Items measuring outcome expectancy (OE) and continuous knowledge contribution behavior (CKC) were both adapted from Shi, Hu [76] and d'Arma, Isernia [77]. Finally, items measuring initial knowledge contribution behavior (IKC) were adapted from Wang, Wang [78] and Mustafa and Zhang [24].

To measure the six constructs in the model, the measurement items were developed as Likert-type statements using a 5-point scale ranging from strongly disagree (1) to strongly agree (5). After developing the questionnaire, this study first tested its face validity by inviting a small sample of 15 users of the surveyed OIC to pretest the questionnaire and to inform if there were any problems such as unclear item content during the completion process. Subsequently, the questionnaire items were modified for specific industries and contexts, and the items were evaluated based on user feedback on their content and wording. As a result, the questionnaire was modified before it was finalized and used in the survey. Table 3 lists the construction of the research model, as well as the associated measures and their sources.

Table 3. Questionnaire measurement indicators and sources.

Constructs	Measurement Items		Source
Observational Learning (OL)	OL1	I like to browse the posts of other users in the community	[72]
	OL2	I follow other users in the community	
	OL3	Before contributing my knowledge, I like to see what knowledge other users have contributed	
	OL4	I am often impressed by the knowledge contributed by users in the community	
Reinforcement Learning (RL)	RL1	The knowledge I contribute to the community is positively responded to by other users	[73–75]
	RL2	The knowledge I contribute to the community is recognized by other users	
	RL3	I usually receive attention from other users after contributing knowledge to the community	
Self-efficacy (SE)	SE1	I believe I have the ability to contribute knowledge to the community	[10]
	SE2	I believe I have the ability to assist other users in the community	
	SE3	I believe I have the ability to provide useful information and comments to other users in the community	
Outcome Expectancy (OE)	OE1	I think contributing knowledge will increase my reputation in the community	[76,77]
	OE2	I think contributing knowledge will make me more respected in the community	
	OE3	I think contributing knowledge will allow me to make new friends in the community	
	OE4	I think contributing knowledge will bring me benefits in the community	
Continuous Knowledge Contribution (CKC)	CKC1	I often participate in knowledge contribution activities in the community	[76,77]
	CKC2	I often provide useful information in the community	
	CKC3	I often contribute knowledge in the community	
Initial Knowledge Contribution (IKC)	IKC1	I will participate in knowledge contribution activities in the community	[24,78]
	IKC2	I will contribute useful information in the community	
	IKC3	I will contribute knowledge in the community	

4.2. Sampling and Data Collection

For the purpose of this study, we chose the Microsoft Power BI open innovation community (https://community.powerbi.com/, accessed on 8 October 2022). The Microsoft Power BI community is a network for professionals and users working in business intelligence and analytics [6]. It was created specifically to connect Microsoft with its user community, crowdsourcing ideas directly from Power BI consumers to drive and develop new solutions and products. Similar to other popular OICs such as Tableau Community, KNIME Community, and Qlik Community, users can join the community for free by creating a profile with an email address. If a user does not provide a username when creating an account, the platform assigns a default username that is anonymous but can be provided by the user at a later date.

The Microsoft Power BI community was selected for this study based on the following criteria. First, the company's innovation performance data is publicly available. As of June 2022, Microsoft has successfully collected 9241 ideas, of which 938 have been successfully implemented, representing 10% of the total number of ideas submitted. Second, the Microsoft Power BI community has a large amount of published content, user comments and other interactive data. Third, the community has a large and diverse user base, with a growing number of users searching, contributing and exchanging knowledge within the community every day. For example, as of April 2022, the Microsoft Power BI community has more than 50 million registered users, with more than 10,000 users active every day. Therefore, it is convenient to find a sufficient sample of lurkers and contributors to study and compare the interaction dynamics between the motivating factors of knowledge contribution behavior in the OIC. In addition, the large user base provided a valuable source of data for previous academic studies [1,3,29]. Therefore, as a successful professional OIC, the Microsoft Power BI community can serve as a typical case study for academic research and provide useful suggestions for the development of other OICs.

The empirical data used to test the hypotheses in this study were collected through an electronic questionnaire developed by Survey Monkey, a web-based application. The link to the questionnaire was distributed to the community by posting it in the Microsoft Power BI community. Participation in this study was conducted on a voluntary basis, and no financial incentives were offered. To prevent duplication of questionnaires, respondents' IP addresses were locked when they completed the questionnaire, and only one copy of the questionnaire was kept for the same address. Of the 1200 questionnaires sent to respondents, 377 were successfully completed, yielding a valid response rate of 31%, a sample acceptable for the structural equation modeling in this study [79].

In this study, the community user base was classified as lurkers and contributors according to Yang, Li [26]. Lurkers were classified as users who had never posted in the community. Conversely, contributors were defined as users who participated in the community for at least three months and posted at least once a month. The entire data collection process lasted for five months (May 2022 to September 2022). Out of the final 377 valid questionnaires, 228 participants were classified as lurkers and 149 participants were classified as contributors.

4.3. Data Analysis

Following the recommendations of Anderson and Gerbing [80], a two-step approach of structural equation modeling (SEM) was used to analyze the data and test the proposed hypotheses. In the first step, confirmatory factor analysis (CFA) was used to first estimate the fit of the measurement model and then to assess the validity and reliability of the measurement model [81]. In the second step, the structural model and hypotheses were tested using SEM (using Amos 26.0). The hypothesized relationships between the constructs within the proposed model were assessed by examining the path coefficients and their significant coefficients. Since the main purpose of the study was to compare the knowledge contribution behavior between lurkers and contributors, a *t*-test was used to determine if the coefficients of lurkers and contributors were significantly different [26].

Structural equation modeling presents two advantages over traditional regression and causal path analysis. First, it provides a systematic basis for assessing the fit of the proposed model to the data using the χ^2 statistic and incremental fit indices such as the non-normative fit index (NNFI) and the comparative fit index (CFI). In addition, absolute fit indices of the mean squared error of approximation (RMSEA) are useful for fit assessment [82]. Second, the procedure allows testing complex multidimensional relationships and estimating structural relationships between conformations without measurement error, both individually and simultaneously.

As suggested by Wolf, Harrington [83], in order to determine whether the specified number of subjects is sufficient to derive statistically significant factor estimates, a sample size of approximately 200 would be sufficient for small and medium-sized models. In the present study, the available response rate was much higher than the generally accepted threshold suggested by Nulty [84]. In addition, in the structural model of this study, the maximum number of measurement items used to measure a single construct is four; therefore, a minimum sample size of 40 is required for SEM analysis, as suggested by Hair, Risher [85]. We also evaluated the minimum sample size requirement using G-Power software, and the results showed that the minimum sample size required to obtain a minimum R^2 value of 0.25 in any single construct at a 5% significance level and 80% statistical power is 90, which is consistent with the minimum sample size recommended by Hair, Hult [79] for SEM applications. Thus, a sample size of 375 is sufficient and large enough for structural equation models to shape the conclusions from this study. The following sections clarify the estimation results of the measurement and structural models.

5. Results

5.1. Demographic Characteristics of Participants

In addition to the items used to measure the constructs in the proposed model (Figure 1), the questionnaire included demographic information about the respondents, including their gender, age, time in the community, and experience in business intelligence and analytics practices. Table 4 summarizes the demographic characteristics of the respondents. The lurker sample consisted of 116 males (50.9%) and 112 females (49.1%), the majority of whom (96%) were between the ages of 21 and 40, indicating that younger people are the primary consumers of business intelligence and analytics products and tools. In addition, the majority of respondents (98%) hold a bachelor's degree or higher. The majority of them (97.6%) had been involved in community activities for less than two years. The sample of contributors consisted of 128 men (56.1%) and 100 women (43.9%). The majority of them (93.4%) were between 21 and 40 years old, and the majority of respondents (97.4%) had a bachelor's degree or higher in education. The majority of them (80.7%) had been involved in community activities for more than six months. This suggests that the demographic characteristics of the lurkers and contributors are largely identical.

Table 4. Demographic characteristics of respondents.

Demographic Characteristics		Lurkers		Contributors	
		Frequency	Percentage	Frequency	Percentage
Gender	Male	116	50.88%	78	53.06%
	Female	112	49.12%	71	48.30%
Age	Under 18 years old	2	0.88%	2	1.36%
	18~25	48	21.05%	22	14.97%
	26~30	116	50.88%	63	42.86%
	31~40	51	22.37%	45	30.61%
	41~50	9	3.95%	7	4.76%
	51 years old or above	2	0.88%	8	5.44%
Education	High school and below	0	0.00%	0	0.00%
	Junior college	0	0.00%	0	0.00%
	College	2	0.88%	6	4.08%
	Undergraduate	193	84.65%	118	80.27%
	Master's and above	33	14.47%	23	15.65%
Community use time	Less than 3 months	53	23.25%	0	0.00%
	3~6 months	83	36.40%	14	9.52%
	6~12 months	72	31.58%	31	21.09%
	1~2 years	10	4.39%	30	20.41%
	More than 2 years	10	4.39%	72	48.98%

5.2. Measurement Model Validation

To evaluate the measurement model, we estimated the reliability and convergent validity of the constructs by calculating Cronbach's α, composite reliability (CR), and average extracted variance (AVE) as a measure of internal consistency [86]. For a construct with adequate reliability, Cronbach's α should be greater than 0.7, CR should be at least 0.6, and AVE should exceed 0.5 [87]. The results of construct reliability and convergent validity tests are shown in Tables 5 and 6, respectively. The Cronbach's α for all constructs was between 0.812 and 0.876, indicating adequate reliability.

Both content validity and construct validity are routinely reported measures of validity. Since the constructs in this study were drawn from the existing literature, they exhibited strong content validity. Construct validity was tested by discriminant validity and convergent validity. Convergent validity was tested by principal component analysis of each measurement item. A measure is high loaded if it has a loading coefficient of 0.6 or more and a cross-loading coefficient of 0.4 or less [86]. According to these criteria, all items had factor loadings above the recommended level of 0.6 and were significant at $p < 0.001$; no items had cross-loadings above 0.4. The composite reliability (CR) values were all greater than 0.7. The average extracted variance (AVE) values were above the acceptable threshold of 0.5; therefore, as shown in Tables 5 and 6, there was sufficient convergent validity for all the constructs in the model.

Discriminant validity was examined using the criterion proposed by Fornell and Larcker [86]; the square root of the AVE of each construct should be greater than the correlation between that construct and the other constructs. As shown in Tables 7 and 8, in our study model, each construct has higher loadings on its corresponding construct than its cross-loadings on the other constructs, thus providing evidence of discriminant validity. Overall, the measurement model showed adequate reliability, convergent validity, and discriminant validity.

Table 5. Construct reliability and convergent validity (Lurkers).

Measurement Item	Standardized Factor Loadings			
	OL	SE	OE	IKC
OL1	0.677			
OL2	0.688			
OL3	0.723			
OL4	0.708			
SE1		0.812		
SE2		0.914		
SE3		0.746		
OE1			0.525	
OE2			0.851	
OE3			0.847	
OE4			0.651	
IKC1				0.817
IKC2				0.715
IKC3				0.877
Cronbach'α	0.788	0.854	0.805	0.850
CR	0.812	0.864	0.814	0.876
AVE	0.512	0.711	0.543	0.656

Table 6. Construct reliability and convergent validity (Contributors).

Measurement Item	Standardized Factor Loadings				
	OL	RL	SE	OE	CKC
OL1	0.706				
OL2	0.840				
OL3	0.655				
OL4	0.572				
RL1		0.707			
RL2		0.812			
RL3		0.658			
SE1			0.770		
SE2			0.760		
SE3			0.701		
OE1				0.514	
OE2				0.874	
OE3				0.903	
OE4				0.601	
CKC1					0.807
CKC2					0.827
CKC3					0.864
Cronbach'α	0.787	0.744	0.783	0.810	0.866
CR	0.802	0.771	0.784	0.822	0.868
AVE	0.504	0.536	0.554	0.556	0.706

Table 7. Discriminant validity (Lurkers).

	IKC	OE	SE	OL
IKC	0.810			
OE	0.406	0.737		
SE	0.432	0.119	0.838	
OL	0.441	0.470	0.461	0.716

Note: Values on the diagonal show the square root of AVE.

Table 8. Discriminant validity (Contributors).

	CKC	OE	SE	RL	OL
CKC	0.840				
OE	0.465	0.746			
SE	0.515	0.339	0.843		
RL	0.585	0.370	0.528	0.732	
OL	0.301	0.309	0.123	0.324	0.710

Note: Values on the diagonal show the square root of AVE.

5.3. Common Method Variance and Multicollinearity Testing

To test for common method variance caused by the measurement instrument, two tests were conducted. First, this study conducted Harman's single-factor test [88] and applied the recommendation of [89] regarding the total variance explained by common factors, which is below a threshold of 50%. The test results explained 33.532%, which confirms that the common method bias in our empirical data was acceptable. Second, the variance inflation factor (VIF) was tested for all constructs to estimate the multicollinearity problem. As shown in Table 8, all VIFs were below 3.3, indicating the absence of multicollinearity problems. According to Lavery, Acharya [89], fully covariant VIFs can be tested for common method bias. Since all VIFs are below 3.3, there is no serious common method bias. The multicollinearity problem is assessed by tolerance and VIF. According to Figueroa-García, García-Machado [90], the threshold value for tolerance is 0.10 and the VIF value is below 10. Table 9 shows that the results of this study meet the criteria for conducting structural model estimation.

Table 9. Common method variance and Multicollinearity testing.

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model	**B**	**SE**	***β***	***t***	**Sig.**	**Tolerance**	**VIF**
Constant	0.061	03285		0.170	0.847		
OL	0.210	0.70	0.178	2.750	0.005	0.557	1.711
RL	−0.137	0.073	−0.104	−1.711	0.067	0.742	1.382
SE	0.236	0.060	0.241	3.482	0.002	0.647	1.216
OE	0.170	0.083	0.108	1.905	0.046	0.681	1.313

Note: dependent variables: IKC and CKC.

5.4. Structural Model Estimation

To assess the extent to which the model represents the data, this study used a series of "goodness-of-fit" indices recommended by Marsh, Hau [91]; namely χ^2/df, RMSER, GFI, AGFI, RMR, NFI, and CF. The results of the goodness-of-fit are shown in Tables 10 and 11, respectively. All indices are above the acceptable thresholds suggested in previous studies [82,92,93], indicating that the model provides an acceptable fit to the data.

Table 10. Model fit coefficients (Lurkers).

Fit Index	χ^2/df	RMSER	GFI	AGFI	CFI	RMR	NFI
Actual value	2.005	0.071	0.867	0.813	0.915	0.041	0.854
Optimal standard value	<2	<0.08	>0.9	>0.8	>0.9	<0.05	>0.9
Fit	Acceptable	Acceptable	Acceptable	Good	Good	Good	Acceptable

Table 11. Model fit coefficients (Contributors).

Fit Indicator	χ^2/df	RMSER	GFI	AGFI	CFI	RMR	NFI
Actual value	1.948	0.054	0.887	0.852	0.927	0.031	0.872
Optimal standard value	<2	<0.08	>0.9	>0.8	>0.9	<0.05	>0.9
Fit	Good	Good	Acceptable	Good	Good	Good	Acceptable

To test the hypotheses and estimate the standardized path coefficients of the study model, the maximum likelihood method [94] was used. As shown in Table 12, most paths were significant in the expected direction. The exception was the path connecting observational learning with contributor self-efficacy (H2b). The path coefficients for H1a, H2a, H3, H4, H5a, H5b, H6a, and H6b were significant at the $p < 0.001$ level, indicating support for these hypotheses. The path coefficient for H1b was significant at the $p < 0.05$ level, indicating support for this hypothesis. H2b was rejected. Figure 2 shows the path estimates for each hypothesis in the study model.

Table 12. Hypotheses testing.

Hypotheses	Path Coefficient	*t*-Value	Test Results
H1a. *Observational learning has a positive impact on the outcome expectancy of the initial knowledge contribution of lurkers.*	0.452 ***	4.223	Supported
H1b. *Observational learning has a positive impact on the outcome expectation of continuous knowledge contribution of contributors.*	0.219 *	2.526	Supported
H2a. *Observational learning has a positive impact on the self-efficacy of knowledge contribution of lurkers.*	0.458 ***	4.422	Supported
H2b. *Observational learning has a positive impact on self-efficacy of knowledge contribution of contributors.*	−0.028 ns	−0.471	Not supported
H3. *Reinforcement learning has a positive impact on the outcome expectancy of contributors to continue contributing knowledge.*	0.344 ***	3.813	Supported
H4. *Reinforcement learning has a positive impact on the self-efficacy of contributors to continue contributing knowledge.*	0.585 ***	5.903	Supported
H5a. *Outcome expectancy has a positive impact on the initial knowledge contribution behavior of lurkers.*	0.399 ***	4.252	Supported
H5b. *Outcome expectancy has a positive impact on the continuous knowledge contribution behavior of contributors.*	0.354 ***	4.585	Supported
H6a. *Self-efficacy has a positive impact on the initial knowledge contribution behavior of lurkers.*	0.433 ***	4.913	Supported
H6b. *Self-efficacy has a positive impact on the continuous knowledge contribution behavior of contributors.*	0.457 ***	5.618	Supported

Note: ns, not significant, * $p < 0.05$; *** $p < 0.001$.

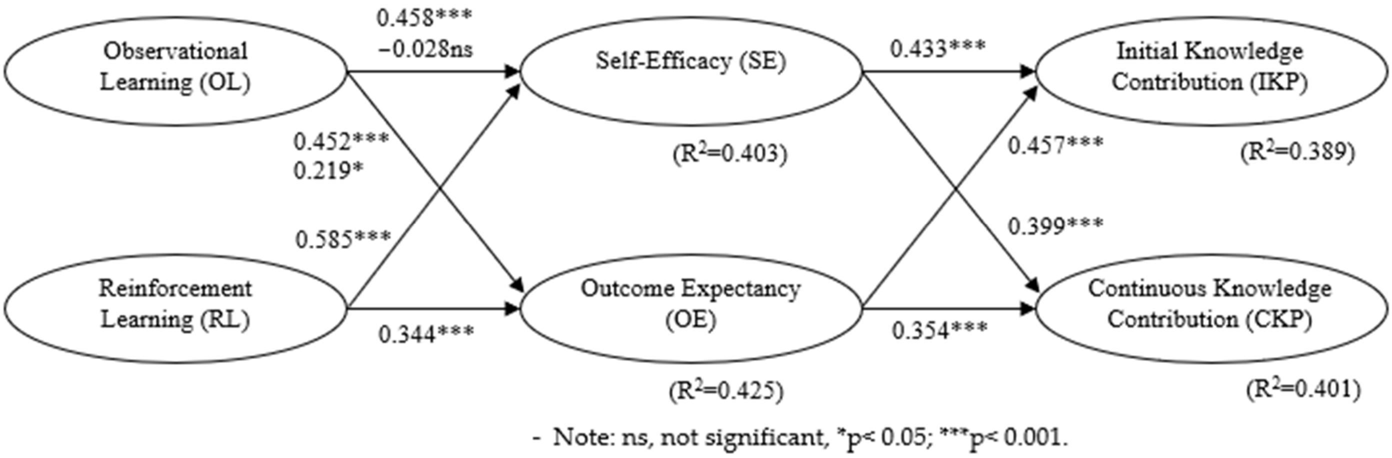

Figure 2. Results of model path analysis.

To examine the differences in the effects of observational learning on the organism cognition between lurkers and contributors, this study used multivariate cluster analysis and examined the differences in path coefficients between lurkers and contributors with the effects of observational learning on self-efficacy and outcome expectancy as sub-models. The results of the analysis in Table 13 show that the path coefficients from observational learning to self-efficacy and from observational learning to outcome expectancy were significantly larger for lurkers than for contributors. This result suggests that the effect of observational learning on the organism cognition is significantly different for lurkers and contributors. The effects of observational learning were significantly greater for lurkers than for contributors, and this difference was particularly pronounced for self-efficacy.

Table 13. Differences in path coefficients between lurkers and contributors.

Path	Path Coefficient		Path Comparison t-Value
	Lurkers	Contributors	
Observational learning (OL)—Outcome expectancy (OE)	0.513 (0.104)	0.283 (0.064)	2.018 *
Observational learning (OL)—Self-efficacy (SE)	0.507 (0.142)	0.115 (0.051)	4.068 ***

Note: ns, not significant, * $p < 0.05$; *** $p < 0.001$.

5.5. Mediation Effect Testing

To examine and analyze the mediating effects of self-efficacy and outcome expectancy between social learning and knowledge contribution behavior, the bootstrapping method was used in this study. The bootstrapping method is a widely used method for analyzing mediating effects in recent studies [1–3] to overcome doubts about the rationality and validity of traditional causal stepwise regression analysis methods [34].

According to the mediating effect analysis for lurkers in Table 14, the confidence interval for the indirect effect in the path of observational learning through self-efficacy affecting initial knowledge contribution behavior was (0.029, 0.306), which contains no 0 and the indirect effect is significant. The confidence interval for the direct effect was (−0.003, 0.543), containing 0, and the direct effect was not significant. Thus, self-efficacy plays a fully mediating role between observational learning and initial knowledge contribution behavior. At the same time, the confidence interval for the indirect effect in the path of observational learning through outcome expectancy affecting initial knowledge contribution behavior was (0.029, 0.259), which contained no 0 and the indirect effect was significant. The confidence interval for the direct effect was (−0.003, 0.543), containing 0, and the direct effect was not significant. Thus, the outcome expectancy acts as a full mediator between observational learning and initial knowledge contribution behavior.

Table 14. Bootstrapping mediation effect analysis (Lurkers).

Path	SE	Indirect Effect	BC 95% Confidence Interval		p-Value	Direct Effect	
			Lower Limit	Upper Limit			
OL-SE-IKC	0.054	0.122	0.029	0.306	0.008	OL-IKC	
OL-OE-IKC	0.046	0.118	0.029	0.259	0.011	−0.003	0.543

Note: bootstrapping sample size is 5000, and bootstrap sampling method is chosen as bias-corrected (BC) method with 95% confidence level.

According to the mediating effect analysis for contributors in Table 15, the confidence interval for the indirect effect in the path of observational learning influencing continuous knowledge contribution behavior through self-efficacy was (−0.072, 0.016), containing 0, and the indirect effect was not significant. The confidence interval for the direct effect was (−0.114, 0.264), containing 0, and the direct effect was not significant. Thus, self-efficacy did not mediate the effect between observational learning and continuous knowledge contribution behavior. Furthermore, in the path of observational learning influencing continuous knowledge contribution behavior through outcome expectancy, the confidence interval of the indirect effect was (0.003, 0.126), which did not contain 0, and the indirect effect was significant. The confidence interval for the direct effect was (−0.114, 0.264), containing 0, and the direct effect was not significant. Thus, outcome expectancy fully mediates the relationship between observational learning and continuous knowledge contribution behavior. The confidence interval for the indirect effect in the path of reinforcement learning affecting continuous knowledge contribution behavior through self-efficacy was (0.021, 0.263), which did not contain 0, and the indirect effect was significant. The confidence interval for the direct effect was (0.101, 0.531), which did not contain 0, and the direct effect was significant. Thus, self-efficacy partially mediated the relationship between reinforcement learning and continuous knowledge contribution behavior. In the path of reinforcement learning affecting continuous knowledge contribution behavior through outcome expectancy, the confidence interval for the indirect effect was (0.013, 0.145), which did not contain 0, and the indirect effect was significant. The confidence interval for the direct effect was (0.101, 0.531), which did not contain 0, and the direct effect was significant. Thus, outcome expectancy partially mediated the relationship between reinforcement learning and continuous knowledge contribution behavior.

Table 15. Bootstrapping mediation effect analysis (Contributors).

Path	SE	Indirect Effect	BC 95% Confidence Interval		*p*-Value	Direct Effect	
			Lower Limit	Upper Limit			
OL-SE-CKC	0.014	−0.012	−0.072	0.016	0.412	OL-CKC	
OL-OE-CKC	0.022	0.036	0.003	0.126	0.027	−0.114	0.264
RL-SE-CKC	0.052	0.125	0.021	0.263	0.021	RL-CP	
RL-OE-CKC	0.021	0.064	0.013	0.145	0.008	0.101	0.531

Note: bootstrapping sample size is 5000, and bootstrap sampling method is chosen as bias-corrected (BC) method with 95% confidence level.

6. Discussion

Drawing on the theoretical lens of social learning theory and stimulus–organism–response (SOR) framework, this study developed a model to understand the formation mechanisms of knowledge contribution behavior in OICs. The model was constructed based on a pathway from environmental stimuli (observational learning, reinforcement learning), organism cognition (self-efficacy, outcome expectation) to behavioral responses (initial contribution, continuous contribution). The empirical analysis showed that the model had a good fit, and most of the hypotheses (H1a, H1b, H2a, H3, H4, H5a, H5b, H6a, H6b) were supported in this study. The exception was the test of hypothesis H2b, which was not supported. The results of this study are discussed below.

For lurkers, the results showed that observational learning had a positive and significant effect on two peripheral variables of organism cognition (self-efficacy and outcome expectancy), as hypothesized by H1a and H2a (refer to Table 10). According to social learning theory, by observing and learning from the behavior of others, learners adapt their behavioral cognition to imitate the behavior of others. Open innovation communities provide accessible, unified sharing platforms where they can easily observe knowledge posts contributed within the community without user access restrictions. For lurkers, indirect experience gained through observational knowledge contributions can increase their self-efficacy and outcome expectancy without any need to refer to direct experience. Thus, lurker observational learning behavior has a very strong effect on self-efficacy and outcome expectancy. This resembles the findings of Le, McConney [32], who stated that community users are less capable of self-learning in knowledge contribution tasks and have little head start in social learning, leading to more feelings of disability and helplessness. The findings of this study are similar to the literature and suggest that the social learning system is a significant predictor of self-efficacy and outcome expectancy in explaining knowledge contribution behavior in OICs.

In contrast, for contributors, the results of this study showed that both observational and reinforcement learning had positive and significant effects on behavioral cognition, as stated in the hypotheses (H1b, H3, and H4). However, the results of the study did not provide sufficient evidence for H2b to demonstrate a positive relationship between observational learning and contributor self-efficacy. One possible explanation for these results is that during the continuous knowledge contribution phase, contributors gained not only indirect experience but also direct experience. According to social learning theory, direct experience signifies the success and outcome of the previous user knowledge contribution behavior and has a significant impact on the user's self-efficacy and outcome expectations. On the other hand, indirect experience can influence contributor outcome expectancy, but has no significant effect on self-efficacy, contrary to our hypothesis. Further, during the continuous phase of participation, users are basically or even completely familiar with the rules of community operation and the difficulty of community participation, and are able to actively participate in the community knowledge contribution activities without external environmental stimuli. Another possible explanation is that the subjects selected for this study were basically highly educated users, representing a relatively knowledgeable group of users in the community. In addition to the initial knowledge accumulation, they already have some control over the knowledge contribution behavior. Therefore, the increased knowledge through observational learning did not significantly stimulate their sense of self-efficacy.

The results of this study confirm that observational learning has different effects on the organism cognition for different types of users at different stages of participation. As shown in Table 11, for both lurkers and contributors, the effect of observational learning on organism cognition was significantly greater for lurkers than for contributors. This implies that during the initial knowledge contribution phase, user observational learning plays a key role in influencing organism cognition. In contrast, during the continuous knowledge contribution phase, the influence of user observational learning on cognition gradually diminished and appeared less important. Furthermore, by comparing the effects of observational and reinforcement learning on self-efficacy and outcome expectancy during the continuous knowledge contribution phase, this study found a significant difference in the correlation coefficient between observational and reinforcement learning in terms of self-efficacy ($-0.028 < 0.585$). The same was reported for outcome expectancy ($0.219 < 0.344$). This implies that the key factor influencing self-efficacy and outcome expectancy during the continuous knowledge contribution phase is reinforcement learning, reflecting the importance of the direct experience of previous user knowledge contribution behavior on the perception of future knowledge contribution behavior. A similar finding was reported by Chapman and Dilmperi [23], who found that subsequent user information-contributing behavior was primarily influenced by their prior behavior, i.e., user behavior was primarily driven by the success of their prior behavior. Thus, observational learning has a strong impact on the behavioral cognition of lurkers, while the impact on the behavioral cognition of contributors seems to be less significant, since reinforcement learning plays a key role.

In addition, self-efficacy and outcome expectancy have different effects on knowledge contribution behavior for different types of users. For lurkers, self-efficacy (0.433) and outcome expectancy (0.399) have similar path coefficients on initial knowledge contribution behavior. This implies that self-efficacy and outcome expectancy can act simultaneously. For contributors, there is a significant difference in the path coefficients of self-efficacy and outcome expectancy on continuous knowledge contribution behavior ($0.457 > 0.354$). This implies that self-efficacy has a greater effect on continuous contributor knowledge contribution behavior than outcome expectancy, which also has a significant effect, but not very significant in comparison. This is consistent with the findings of Kim, Salvacion [36], who reported that knowledge acquisition and contribution in virtual communities are indirectly influenced by perceived self-efficacy and outcome expectations of community members.

7. Implications

7.1. Implications for Research

The results of this study provide useful implications for research on open innovation and knowledge management of innovation practices. First, this study contributes to a more comprehensive theory of open innovation participation by deriving participatory knowledge contribution behavior from the perspective of social learning processes. Drawing on the SOR model and social learning theory, this study identifies contrasting antecedents that influence contributor and lurker participation in open innovation. In this respect, this study advances the previous literature by systematically theorizing and validating the different antecedents of contributor and lurker participation in OICs. Furthermore, the results of this study provide a theoretically informed explanation for the nature of lurkers, which is understood much less than contributors in the existing literature [9,32].

According to previous studies, lurkers are viewed as selfish hitchhikers [40] or individuals who rationalize their lurking behavior by not contributing to the information overload of the community [95]. By understanding lurkers as observers with similar psychological scaffolding, this study found that lurkers can gain self-efficacy and motivation to learn by observing the successful contributions of other users in the community. In this way, this study provides a new perspective for studying user knowledge contributions in professional open innovation communities.

Second, this study advocates leveraging OICs as a means of informal knowledge management and sharing. Community management emphasizes the impact of community dynamics, trust, and values on continuous member engagement. In addition, the development of practical activities, informal networks, and leadership roles are important for knowledge management and learning outcomes in OICs. While there are mixed results on the effectiveness of OICs as a knowledge management tool, there is a general consensus that OICs provide an effective way to transfer and share tacit knowledge. Although there is a large body of literature on knowledge sharing, a thorough investigation of its contents reveals that most of the literature essentially explores the act of knowledge contribution and the way in which this knowledge is formed and acquired as separate entities. This study confirms previous research that argues that knowledge contribution and knowledge acquisition are inseparable, interacting organismic entities [51,52,58]. In addition, scholars generally agree that OICs are effective tools for fostering and facilitating the learning process, and that the design of the learning environment is critical to the development and sustainability of the community. Therefore, this study responds to the recurring research gap related to the way these tools needed for social learning are implemented in the context of community technology design through corresponding empirical research.

Finally, this study concludes that OICs can be viewed as a particular type and application of social support systems. Sustained knowledge sharing and social learning by users is predicated on sustained use of and sustained participation in online technologies and communities. In this context, the results of this study provide valuable insights into the continuous use of social support systems that can be used to analyze the continuous knowledge behavior and social learning activities of online community users. Compared to the large and well-established literature on continuous use, there is very little research on the social support aspects of OICs. Furthermore, most of these studies have focused on exploring continuous knowledge contribution or knowledge sharing. Research on continuous use confirms that two central variables, perceived usefulness and satisfaction, have a strong influence on the willingness to continuously use. This study examines knowledge contribution behavior in OICs through the lens of social support mechanisms, providing a new and different perspective for examining the impact of OICs in promoting innovation and landscape in companies, which has implications for research on continuous knowledge sharing involving multiple behavior such as continuous knowledge contribution, continuous knowledge search, and reuse.

7.2. Implications for Practice

The results of this study provide useful implications for the practice and management of open innovation communities. First, this study informs practitioners to design more comprehensive and customized interventions to increase the level of participation in open innovation. At the initial participation phase, observational learning by lurkers can indirectly influence initial contribution behavior through self-efficacy and outcome expectancy. This implication suggests that community managers, as a role model influence, can be used to reinforce observational lurker learning from key contributor behavior. For example, when users post online, the system can promptly remind users they follow or friends of lurkers to participate in a certain activity or post on a certain topic. In addition, the community site can add a list of rewards and promptly announce the reward results after a user posts a high-quality post. By establishing an accurate and effective content recommendation mechanism, relevant and high-quality knowledge posts and community practice activities are recommended to users based on their information search patterns. Accordingly, in the process of observation and learning, lurkers will be exposed to more high-quality and interesting knowledge posts and learn more about the practical activities of central users. Only in this way can their indirect experience and knowledge level be improved and their intrinsic knowledge needs be satisfied, thus increasing their self-efficacy and, in turn, their willingness and behavior to contribute knowledge. In addition, transparent incentive strategies should be developed to reward and encourage those users who post timely and high-quality knowledge posts. For example, virtual gold coins are rewarded to increase user rating and give opportunities to download knowledge for free. In this way, in the process of observational learning, lurkers can perceive the rewarding behavior and raise the outcome expectations, accordingly, thus promoting their knowledge contributions.

Second, community managers need to recognize that reinforcement learning can indirectly influence the continued contribution behavior of active contributors during the continuous participation phase through self-efficacy and outcome expectancy. Therefore, interaction, support, and positive feedback among community peers are critical in the reinforcement learning process. Community managers should use rewards to encourage community members to interact, and can also design easy feedback systems to facilitate communication and interaction among users. In addition, there should be appropriate penalties for malicious comments and negative feedback to guide the community into a positive and healthy learning and communication atmosphere. As with the observational learning effect, rewarding contributors who publish high-quality knowledge and central users who actively participate in practical activities can also greatly enhance contributor self-efficacy and outcome expectancy. Therefore, the community should occasionally conduct practical activities involving central contributors, as direct experience is a major factor in increasing sustained user knowledge contributions. Practical activities can take many forms, both online and offline, all aimed at improving direct member experience and knowledge. Community managers should design practical activities appropriately and publish timely announcements of practical activities and presentations of achievements.

Finally, according to the empirical results of this study, social learning and knowledge contribution are the two major practical activities of OICs. They are both important manifestations of community values and two cornerstones of community development. The knowledge sharing theory based on the traditional innovation environment can no longer adapt to the development of emerging technologies and environments. This study emphasizes the significance of the construction, validation, and development of social collaborative knowledge behavior and knowledge sharing environments. In addition, mechanisms such as structural characteristics of the social networks formed by OICs participants and heterogeneity of participants influence the users' willingness to share and continuously participate in knowledge, as well as the evolution of user knowledge contribution, search, and reuse behavior over time. The interconnection and influence mechanisms of user knowledge contribution behavior over time and how to promote the effectiveness of continuous knowledge sharing in OICs from the perspective of knowledge formation mechanisms are key questions that can be explored based on the findings from this study.

8. Limitations and Future Research Directions

Notwithstanding the implications for research and practice discussed above, the present study has a number of limitations that should be considered in future research. The first limitation of this study is due to the inherent sampling method and the measurement instruments used. The self-administered questionnaire and the subjective measurement of the dependent variable (initial knowledge contribution and continuous knowledge contribution behavior) are subject to bias [82]. The influence of social learning processes in OICs may be diluted or obscured by other general factors when only environmental stimuli are considered. Other important factors that complement knowledge contribution, such as social network structure and competence, should be investigated and incorporated into the model.

Another limitation that may hinder the generalizability of the study results is that the sample of study participants was drawn from only one type of OICs, namely professional OICs from the ICT industry (the Microsoft Power BI community). Nevertheless, there are also OICs focused on crowdsourcing ideas for business intelligence and analytics products, such as Tableau community, KNIME community, and Qlik community [1], which receive a large number of ideas on a daily basis and use a similar vetting mechanism. The findings and recommendations presented in this study can be applied to other communities, as long as they use similar social learning mechanisms as the community used in this study.

Future research should also validate the results of this study in different industries and investigate different patterns of knowledge contribution behavior. Applying the model developed in this study in different research settings will also provide an opportunity to compare between different types of services and collaborations. In future research, it may be interesting to investigate whether similar results related to knowledge contribution occur in other settings and other forms of online engagement. For example, it would be interesting to conduct a longitudinal study to examine how participation in knowledge contribution behavior transforms the members' learning styles over time.

9. Conclusions

Despite the prominent evidence that OICs drive innovation patterns and capabilities of firms, there is still a dearth of studies investigating and comparing the mechanisms that shape the social learning and knowledge contribution behavior of lurkers and active contributors. This study presented a model to understand and compare the influencing mechanisms of two social learning processes, observational learning and reinforcement learning, on the knowledge contribution behavior of lurkers and contributors during the initial and continuous participation phases. Empirical analysis of the data collected from the Microsoft Power BI community revealed that observational learning had a significant effect on lurker organism cognition during the initial participation phase and only indirectly influenced initial knowledge contribution behavior through self-efficacy and outcome expectancy. During the continuous participation stage, observational learning had a significant effect on contributor organism cognition and only indirectly influenced the continuous knowledge contribution behavior through outcome expectancy. In contrast, contributor reinforcement learning, as a key cognitive driver affecting the organism, also partially influenced continuous user knowledge contribution behavior through the mediating role of self-efficacy and outcome expectancy. However, compared to outcome expectancy, the influence of self-efficacy on continuous contributor knowledge contribution behavior was more pronounced than that of lurkers.

The findings from this study provide empirical evidence for the central role of social learning mechanisms in facilitating initial and sustained user knowledge contributions, while also illustrating the interaction dynamics among the motivational factors of knowledge contribution behavior in open innovation communities from a social learning theory perspective. Importantly, this study informs the management of open innovation communities on how to attract lurkers, as these communities need to compensate for the loss of contributors and make them more effective through greater leverage. It also highlights development strategies on how to sustain lurker engagement by facilitating the transformation of lurkers into knowledge actors and reducing membership attrition, thereby promoting co-creation and transforming crowd-generated ideas into productivity. This is particularly important in the context of open innovation practices, where openness, interaction, ideation, and sharing of resources with other contributors in the community are critical to the sustainability and invocation performance of the community.

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