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The Impact of Linguistic Complexity on Leadership in Online Q&A communities: Comparing Knowledge Shaping and Knowledge Adding

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ABSTRACT

Understanding how to enhance online leadership in online Q&A communities is important because an online leader plays a role model or knowledge coordinator who can strengthen member commitment in the community. Considering the essential role of communication in establishing leadership, this study aims to understand how the linguistic complexity of two types of knowledge contribution, i.e., knowledge adding (KA) versus knowledge shaping (KS) that are targeted at two types of audience, may influence leadership in online Q&A communities. By analyzing the posting history of members from StackExchange, a massive network of online Q&A communities, our findings suggest that among the three linguistic complexity dimensions, readability and lexical diversity of KA have more positive impacts on online leadership than those of KS. However, the sentiment of KS has a more positive impact than the sentiment of KA. This study contributes to the online leadership research by highlighting the importance of adjusting linguistic styles based on types of communication behaviors (i.e., KA and KS) to earn leadership.

1. Introduction

Online communities, supported by the widespread use of social media and digital platforms, have become important venues where people can connect, communicate, and exchange knowledge. Their focus may vary, ranging from creating and sustaining social ties (e.g., Facebook) to knowledge integration (e.g., Wikipedia), sharing of opinions/news (e.g., Twitter), and answering questions (e.g., Quora). These online communities can be viewed as a new form of organization, significantly different from traditional organizations with clear divisions of work and managerial functions [1–3]. They are characterized by fluid boundaries and high turnover as participants can join and leave freely without obligation [4,5]. This is particularly true for online question-and-answer (Q&A) communities, which are largely formed by strangers who share common interests [6] and seek a forum for providing and accessing knowledge [7].

Online Q&A communities like Quora and StackExchange have become essential platforms for knowledge exchange among diverse Internet users [8,9]. For example, on Quora's Q&A community approximately 300 million active users contribute knowledge every month. These communities have steadily gained in popularity because of the quality content hosted on these sites [10] and to make up for the deficiencies in web search engines for acquiring customized information and knowledge [11]. In an online Q&A community, members are able to pose their questions in natural language to receive personalized answers from knowledge providers [6]. Members may also play varying roles in different interactions (e.g., as a knowledge seeker, a knowledge provider, and a moderator), and the alignment of member participation and the platform's business goal are facilitated by feedback and reward systems (e.g., reputation scores and badges). The Q&A platform may also provide algorithmic matching mechanisms to facilitate information exchange (e.g., automatic post recommendation algorithms). Although online Q&A communities have gained increasing popularity, their sustainability largely depends on online leaders who play significant roles in facilitating knowledge exchange and maintaining high-quality knowledge flow in the community [5, 10, 11].

Understanding how to enhance online leadership in a Q&A community is important because the primary objective of such communities is to facilitate knowledge exchange, but such a process is largely voluntary and self-organized. Recognized leaders often serve as role models within the community. Their frequent participation may facilitate other members' knowledge contribution [12,22]. Their high-quality

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knowledge contribution sets a standard that other members may follow. Online leaders also develop effective ways to operate a community and sustain community activities [5]. For example, leaders may strategically adjust their contribution behaviors to meet the varying demands of online communities. In addition, the leadership status they achieve may motivate other members' commitment to the community [14]. Some platforms also allow leaders to access advanced features for enhanced knowledge distribution and integration. For example, StackExchange unlocks features like removing duplicates and adding tags if a member achieves a higher level of reputation status. In this case, member-selected leaders perform the role of a platform coordinator to enhance the quality of knowledge distributed across the entire community. Thus, leaders in online communities play important roles in facilitating valued knowledge exchange and creating a culture that engages members and sustains the community.

While extensive research has enriched our understanding of organizational leadership, much less is known about leadership in the new form of online community organization [4,12]. A leader in an online community can be formally or informally hired by the platform (e.g., a platform manager or official moderator who takes care of the community operation) or selected by the community members. The latter type tends to be the focus of online community leadership research [4,13,14], and it is particularly important in Q&A communities to facilitate and regulate members' voluntary knowledge contribution given the community's self-organizing nature [15–17]. Although different online Q&A communities have different processes for how members identify leaders, they share a common mechanism – using reputation systems to recognize members' contributions. Those who rank highly in the reputation system are regarded as leaders [18–20]. The current study adopts this approach to define online leadership as a member's extent of recognition and endorsement from other online community members [4,21]. Such recognition and endorsement are reflected in members' reputation scores earned due to their knowledge contributions voted by other members in the community.

Existing online leadership research has investigated various behavioral, social, and linguistic characteristics that contribute to the emergence of leadership in online communities [4,21]. While the online leadership literature suggests consistent findings regarding the positive roles of knowledge contribution behaviors [14,21] and social network ties [4,17], findings remain ambiguous regarding how linguistic aspects of knowledge contribution influence online leadership. For instance, readability and lexical diversity have been found to have both positive and negative impacts on online leadership [4,17,23,24]. Additionally, research into the linguistic styles of knowledge contribution is relatively limited in the online community context, despite its importance being well recognized in organizational leadership research [25–27]. Arguably, linguistic style may be even more important in determining leadership in online Q&A communities where text is the primary means of communication, void of body language, and other non-verbal communication.

To address this gap in the extant literature, we propose an integrative view of online community leadership that considers both the type of knowledge contributed and how the knowledge is communicated to the audience. In terms of knowledge type, we distinguish between two types of behavior in online Q&A communities: *knowledge-adding (KA)* and *knowledge-shaping (KS)* behaviors. KA contributes new knowledge and perspectives to the existing repository of an online community [28,29], whereas KS provides constructive feedback and suggests modifications to existing knowledge in the online community [28]. Extant research has mainly considered KA or aggregated knowledge contribution such as the total number of posted messages [17] or technical contributions (e.g., adding software code) [14,21] while ignoring the nature of knowledge being contributed. Differentiating between KA and KS allows us to gain deeper insights into how online leadership may emerge from different types of knowledge contributions.

Knowledge contribution behaviors (KA or KS) have distinct audiences (i.e., knowledge seekers who ask questions versus other knowledge contributors who answer questions), which may have different knowledge requirements (e.g., multiple perspectives versus constructive feedback) and levels of expertise (e.g., limited versus in-depth knowledge on the topic under discussion). The effects of KA or KS communication to these distinct audiences can differ significantly depending on how the message is communicated to that audience [30–32]. Drawing from communication accommodation theory (CAT) [33,34], we argue that linguistic styles of knowledge contributions should be attuned to the communication audience to foster leadership in online communities. When communication styles are appropriately adjusted to an audience, the community member is more likely to obtain approvals (represented by up-votes and reputation scores), directly impacting online leadership status. Additionally, depending on the audience's needs and goals, how the knowledge is conveyed (i.e., linguistic characteristics or styles) may play a significant role in their knowledge absorption and quality evaluation [35,36]. Adjusting linguistic styles (such as linguistic complexity and sentiment) to fit the audiences can facilitate communication effectiveness and increase the likelihood of being recognized as a high-quality contribution, which, in turn, results in a higher reputation score for leadership determination.

In the following sections, we briefly review the literature on online leadership and describe our theoretical lens that informs our hypotheses development. Thereafter, the research context and methods are explained. Next, the research results and summary of our hypotheses testing are presented. The final section concludes the paper with implications for research and practice as well as limitations and future directions.

2. Literation Review and Theoretical Background

Previous online community studies largely focused on three theoretical perspectives to explain leadership characteristics and emergence. Firstly, the behavioral leadership perspective focuses on behaviors that a leader performs [37]. For instance, knowledge contribution activities have been widely identified as essential for online leadership [21,22]. The behavioral leadership perspective provides insights on what online community activities leaders engage in while often ignoring how they perform these activities.

Secondly, the network leadership perspective emphasizes the network connections of leaders [38,39]. This view of leadership has been applied in online leadership settings [4,17,40,41] to explain how network characteristics, such as centrality and bridging, contribute to online leadership. However, it has been criticized for ignoring the content being communicated within the network [21].

The third perspective is the communicative leadership perspective [42,43] which focuses on online leadership formation from how messages are communicated and their linguistic styles [4,17,44]. While online leadership literature suggests consistent findings regarding the positive roles of knowledge contribution behaviors [14,21] and network ties/connections [4,17], findings remain ambiguous regarding how linguistic aspects of knowledge contribution influence online leadership. For instance, both positive and negative impacts have been found regarding how readability influences online leadership [4,17,23,24]. Lexical diversity has also been found to influence online leadership in both positive [17] and negative [4] manners.

Leadership behavior in an online community is manifested largely through posting activities, which is a type of communication. As such, the boundary between leader behavior and leader communication may not be clear-cut. In the context of online Q&A communities, principle activities focus on knowledge exchange and communication of knowledge rather than relationship building [45,46]. Thus, here, we focus on the behavioral leadership and communicative leadership perspectives. We posit that an integrative view is needed because the online leadership is influenced by different types of knowledge contribution behaviors and how each type is communicated to its respective audience. In the next subsections, we first explain two types of knowledge contribution behaviors – knowledge-adding (KA) versus knowledge-shaping (KS) behaviors – as antecedents of online leadership, as well as different audiences they target. Then, we explain why accommodated communication is needed depending on the type of knowledge contribution and how such accommodation might be achieved through the adaptation of linguistic complexity.

2.1. KA and KS as antecedents of online leadership

The behavioral leadership perspective [37] emphasizes that online leadership primarily emerges from a member's knowledge contribution behaviors [46,47]. Although different platforms have varying ways of defining their knowledge contribution leaders (e.g., different reputation scoring systems), there are two common types of contribution mechanisms. The first is answering new questions posted by other knowledge seekers in the community, which is defined as KA behaviors [28]. Over time, knowledge contribution leaders emerge as those members who answer questions frequently, and the quality of their answers is high enough to obtain up-vote or best-answer scores from other community members. KA is considered a direct antecedent of online leadership [21, 48], largely due to the rules set by the platform, which rewards members' contributions by assigning reputation scores. Such rewards may also include badges and leadership boards that quantify the knowledge contributions by counting members' high-quality participation (e.g., number of accepted answers and being up-voted).

The second type of knowledge contribution in online communities is through KS behaviors. Instead of answering a question, members can comment on existing posts, aiming to provide constructive feedback, correct errors, or indicate one's agreement and disagreement [45]. In practice, many online community platforms consider KS as secondary contributions [49,50], and thus KS is often not directly rewarded by the platform. However, KS can help members increase exposure, showcase expertise, build relationships, and maintain identities [51]. When members offer comments to other knowledge contributors, they gain online visibility [52], which can help attract recognition and social influence in the community [53]. Additionally, KS behaviors can help develop and retain high-quality knowledge in online communities by constructively modifying other members' knowledge contributions [21] to gain different perspectives and deepen understanding of the topic [51].

While online community leadership literature tends to focus on KA behaviors or aggregate knowledge contributions (such as the total number of posts) [17], we posit that online leadership may also emerge from KS behaviors, given its ability to help members showcase their expertise, increase their exposure, and further their recognition within the community. Differentiating between KA and KS allows us to gain deeper insights into how online leadership may emerge from different types of knowledge contributions.

2.2. Communication accommodation theory and different audiences of knowledge contribution behaviors

When contributing knowledge, it is the audience that determines the value of the knowledge and, thus, the reputation and leadership status of the knowledge contributor. Different types of knowledge contribution behaviors (KA or KS) are targeted toward different audiences, which may necessitate different communication styles. As such, from the communicative leadership perspective, we draw on CAT [33] to argue that knowledge contributors should adopt different communication styles depending on the designated audience for that contribution behavior. Contribution behaviors that are accommodated to the audience can help a knowledge contributor gain audience approval and achieve leadership status in the community.

Initially developed by Howard Giles, CAT posits that communicators attune their communication according to the characteristics of the recipients [33,34]. By seeking convergence and accentuating divergence in communication styles between the focal communicator and the interlocutors, the communicator can increase communication efficiency, maintain social identity, and obtain social approval [33]. Communication accommodation has been widely applied in leadership communication research to explain leader effectiveness [27,54,55]. Leaders may apply an audience segmentation strategy to tailor the languages or metaphors used for different segments to better exert opinion influence [25,26]. To obtain online leadership, we expect accommodated communication reflected in the posts' linguistic characteristics to be a significant contributor because the online expression is largely the only approach for a member to be recognized by and influence others. Although the communication accommodation perspective has been applied in the online community context [56], limited attention has been paid to understand how communication accommodation can enhance online leadership.

Table 1
Comparison of two types of knowledge contributions in online Q&A communities.

	Knowledge adding (KA)	Knowledge shaping (KS)
Key behaviors	Initiate a thread to answer an unsolved question	Comment on existing threads to provide feedback, corrections, and criticisms to existing answers
Main audience	Knowledge seekers who post the question	Other knowledge contributors who post the answer
Expected level of expertise of the audience	Limited knowledge on the topic under discussion	Have a good understanding of the topic under discussion
Level of tensions and conflicts	Minimal	Considerable

In our context of online Q&A communities, members may have three types of roles: *knowledge seekers* who post questions, *knowledge contributors* who answer the questions, and *knowledge shapers*[1] who provide feedback or modify the posts written by other knowledge contributors. They have different motivations to participate, and they communicate to different audiences who have varying levels of expertise [28] – an accommodated communication style should help them better communicate their information and achieve their goal. For members who perform KA, their knowledge contribution mainly serves as answers to the unsolved questions in online Q&A communities. Thus, their primary audience is knowledge seekers who have limited knowledge of the raised question [49]. On the other hand, for members who perform KS, their knowledge contributions mainly serve as comments, feedback, corrections, and criticisms to existing answers [28]. Thus, their primary audience is other knowledge contributors who already provided answers and thus have a good understanding of the topic under discussion [57].

The online community literature suggests that compared with KA, KS may involve more tension and divergence between the members during the KS process [58,59]. Tension tends to be minimal during KA since multiple perspectives are often valued, and conflicts regarding changing existing knowledge contributions do not tend to exist. However, more conflicts may occur in knowledge exchange and retention during KS because community members are often reluctant to revise their proposed answers [59–61]. For instance, in technical online communities, conflicts may arise when a member identifies an error in the technical document, but the document author may disagree with the critiques and be reluctant to change [62]. Table 1 provides a summary of the differences between KA and KS behaviors and their primary audiences.

[1] Knowledge-shaping behaviors can be considered as knowledge contribution. We use two different labels (i.e., knowledge contributor versus. knowledge seeker) to highlight the differences in knowledge contribution behaviors (i.e., knowledge adding versus knowledge shaping).

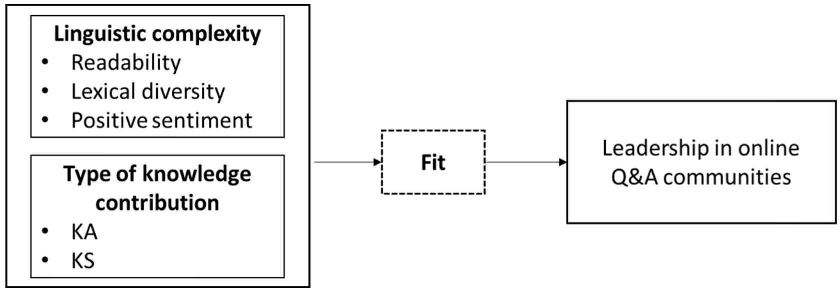

Fig. 1. Conceptual model
Note: the solid boxes represent the constructs empirically examined, whereas the dotted box represents our theoretical mechanism.

2.3. Linguistic complexity as a communication accommodation mechanism

Informed by the communicative leadership perspective [42,43], we consider linguistic complexity a critical communication accommodation mechanism. For different audiences – considering their levels of expertise and potential tensions – knowledge should be communicated in a way to fit their needs and attenuate the potential tensions. Linguistic complexity contains three dimensions—morphology complexity (e.g., readability), lexicography complexity (e.g., lexical diversity), and semantics complexity (e.g., sentiment) [63]. Morphology complexity focuses on the structural complexity of words, such as the number of words, the number of characters in words, and the number of syllables per word [64]. It is often represented by readability which is the ease of understanding written text [65,66]. Lexicography complexity focuses on the range and variety of vocabulary used in a given text [67], which is often represented by lexical diversity. Lastly, semantics complexity refers to the complex meaning of a written text [68]. Various semantic concepts can be extracted from a written text [69]. A simplified way to interpret these semantic concepts is to link them with positive or negative sentiments [69–71], which is the approach we adopt in the current study.

Previous studies have found that linguistic complexity plays a significant role in digital communication [64,72]. For instance, linguistic complexity can reflect an individual's range and sophistication of languages, which signal the individual's expertise and facilitate others' engagement in an online community [72]. Linguistic complexity can also help to efficiently describe different opinions and values, strengthening social bonds during online communication [73]. In addition, different roles can be enhanced and maintained through linguistic complexity. For instance, Sivanaesharajah [74] suggests that when online community members shift their roles from knowledge seekers to knowledge givers, their linguistic complexity increases significantly, reflected in increased lexical diversity and information embedded in their posts. By contrast, linguistic complexity may also impose a greater cost on readers such that the posts will be difficult to understand and hence less likely to be read and responded to [75]. However, lack of linguistic complexity may reduce the perceived reasoning of a post [71,76], such that readers' trust and recognition of the post would also be attenuated.

Taken together, linguistic complexity significantly influences audiences' understanding and engagement of the posts, which affects members' evaluation and recognition of the posts being up-voted or selected as the best answers. Hence, online leaders need to accommodate their linguistic complexity if they want to obtain more recognition from community members. However, the direct impacts of linguistic complexity on online leadership are ambivalent – for example, while linguistic complexity hinders the understandability of the information, it may also help to infer information providers' expertise, influencing community members' acceptance and perceived helpfulness of the information. To this end, we argue that the impacts of linguistic complexity should be examined in conjunction with the type of knowledge to be communicated because the desire and acceptance for linguistic complexity are different for different communication purposes and audiences. We propose our hypotheses in the following section. For each type of linguistic complexity, we first explain why the direct impact may be ambivalent, and then we explain how the benefits (or the challenges) of each type of linguistic complexity may become more salient under KA (or KS), highlighting the importance of fit between linguistic styles and knowledge contribution behaviors in promoting online leadership.

3. Hypotheses Development

Fig. 1 below presents our conceptual model. We posit that online leadership benefits from accommodated communication, coming from the fit between the type of knowledge contribution and the linguistic style represented by three types of complexity. The fit concept captures the "ideal" linguistic profiles of KA versus KS for their respective audiences. As previously outlined, the main audience of KA behaviors is

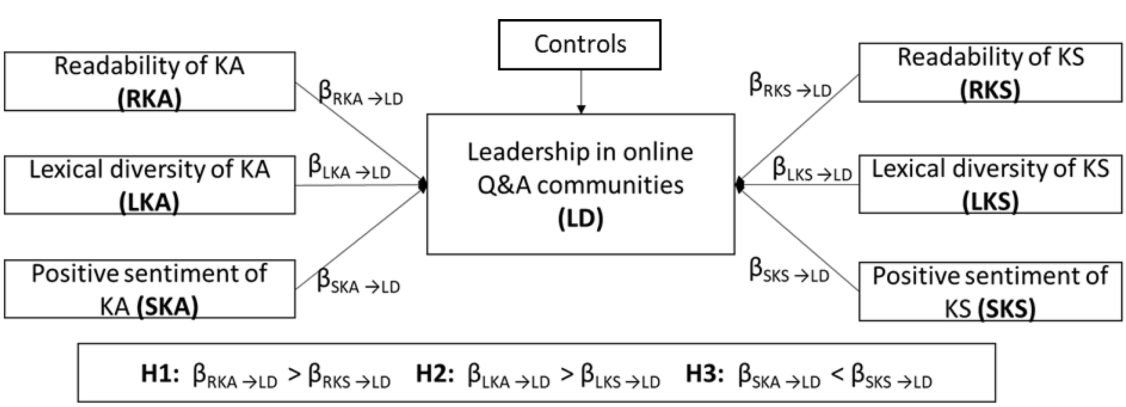

Fig. 2. Research model.

Table 2
Summary of construct definitions

Concept	Description
Leadership in online Q&A communities	The extent of reputation-based recognition from other community members.
Readability of KA	Ease of understanding the KA posts as reflected by the posts' morphology complexity.
Readability of KS	Ease of understanding the KS posts as reflected by the posts' morphology complexity.
Lexical diversity of KA	Vocabulary richness of the KA posts as reflected by the posts' lexicography complexity.
Lexical diversity of KS	Vocabulary richness of the KS posts as reflected by the posts' lexicography complexity.
Positive sentiment of KA	The degree of positive emotional tone of the KA posts.
Positive sentiment of KS	The degree of positive emotional tone of the KS posts.

knowledge seekers who post new questions, whereas the main audience of KS behaviors is other knowledge contributors who have provided answers or comments to posted questions. Thus, we expect systematic differences in KA and KS's linguistic styles, which contribute differently to online leadership.

Our proposed approach of measuring fit is through a profile analysis [77], focusing on comparing linguistic features of the same group of individuals across different scenarios (e.g., KA and KS). That is, members are "successful" or "less successful" in obtaining leadership depending on the patterns of consistency between their knowledge contribution behaviors and linguistic styles. Empirically, the impacts of fit and non-fit are detected by comparing coefficients of each linguistic style-knowledge contribution pair. Here, linguistic complexity, two types of knowledge contribution, and online leadership are all conceptualized at the individual level. Fig. 2 presents our research model, and Table 2 presents core construct definitions.

3.1. Readability and the online leadership from KA versus KS

The first dimension of linguistic complexity is readability. Existing literature suggests an ambivalent impact of readability on online leadership. In the online community, readability positively influences online leadership because brevity and succinctness in expression promote effective communication; hence, the posts are more understandable and more likely to be accepted by others [4]. However, a moderate level of readability (i.e., an inverse U shape impact of readability) has been found to enhance online leadership in the context of online reviews [23], because high readability may imply limited effort in writing the review, while low readability results in difficulty in understanding reviews. In addition, negative impacts of readability on leadership have been reported in online contexts. Longer emails (i.e., lower readability) are associated with leadership in virtual teams because they represent more involvement in task-oriented behaviors, contributing to a member's influence in the virtual team [24]. The linguistic style of a post with low readability (using more advanced words and more complex sentences) could imply that the writer is more educated and has more mature linguistic skills [76]. Furthermore, members often pay less attention to short and simple sentences, assuming they contain less useful content, and hence low readability may contribute more quality recognition and online leadership [78].

According to the CAT, the effects of readability may depend on the communication audiences' ability to understand the message. Prior research [79] suggests that communication audiences' background knowledge determines the relative importance of message readability. When the audience is familiar with the topic, readability becomes less concerned. By contrast, when the audience has limited background knowledge, readability plays an essential role in helping the audience comprehend the messages. The main audience of KA is the knowledge seekers who are unfamiliar with the topic and thus post the questions to seek new knowledge. If the answer is written in a complex manner, knowledge seekers may not have sufficient knowledge to comprehend it. Thus, they cannot recognize the contribution of KA with low readability. By contrast, if the answer is written in a readable way, knowledge seekers can easily absorb the message, which increases the likelihood of being recognized as a helpful post (i.e., get an up-vote or be selected as the best answer). Such recognition contributes to reputation-based online leadership.

The main audience of KS, on the other hand, is knowledge contributors who have posted answers to the questions raised in online Q&A communities. These audiences already have sufficient knowledge of the topic, and readability is not a primary concern for comprehending the message. As an illustration, a previous study [80] has found that the readability of financial disclosure influences readers' earnings judgment depending on their level of background knowledge. The negative aspects of high readability, such as being interpreted as a lack of expertise or effort, would be more salient for KS than KA. Since the audience of KS often has in-depth knowledge of the topic, they may have a higher tendency to interpret highly readable posts as coming from a contributor with lower expertise, lower linguistic sophistication, and lower level of education [23,76]. In addition, the threats of being neglected due to overly simple content (i.e., high readability) are more salient for KS than KA because KS is a secondary contribution that receives less community interest in general [78], and being neglected by other members may make KS too peripheral to be considered as a driver for online leadership. In summary, we posit that high readability is more beneficial for KA, while for KS, high readability may not be as valued by its audience (i.e., non-significant or negative impacts). Thus, H1 is proposed as follows:

H1: The readability of KA has a more positive impact on leadership in online Q&A communities than the readability of KS.

3.2. Lexical diversity and online leadership from KA versus KS

The second type of linguistic complexity we consider is lexical diversity. Lexical diversity reflects the variety of words used in a message [4,81]. Similar to readability, the impact of lexical diversity on online leadership is expected to be ambivalent. Previous studies [4,17,82] suggest that individuals with a broader linguistic range and higher diversity are perceived as more credible and may exert more influence than those with less linguistic diversity in an online context. As Bradac et al. [83] noted, diversity affects the audience's judgment of a speaker's intellectual and communicative ability as well as his/her social status. Leveraging lexical diversity may be beneficial in elaborating the messages and expressing them from multiple perspectives. Therefore, lexical diversity can help the leaders gain approval from others if they want to communicate complex ideas that need in-depth elaboration and multiple perspectives. As an illustration, in an online crowdsourcing community, the winning ideas are often those submissions using more unique and lexically diverse language [50]. In this way, both KA and KS may benefit from lexical diversity. However, lexical diversity may also be harmful because the audience may feel unnecessary complexity where a simple principle is described in a complicated way. For example, adding synonyms, expressing the same idea in a wordy manner, and using unique technical terms increase lexical complexity but are often perceived as unnecessary. Such additional complexity may hinder the audience's comprehension and acceptance of the core message [4,84,85]. Similarly, lexical diversity is at its highest level when all words within a text are unique [67,86]; however, new and unique words may hinder communication effectiveness, resulting in increased comprehension difficulty and decreased text cohesiveness [87].

We propose that the audience's information needs may determine the relative importance of lexical diversity; hence, audiences for KA and KS may value information elaboration and multiple perspectives differently. The benefits of complexity will be more valued for knowledge seekers who have limited knowledge on the topic (i.e., audiences for KA). If the answer can be explained with rich elaboration and multiple perspectives, it is more likely that the answer will be perceived as helpful and credible. Lexical complexity facilitates the illustration of different perspectives with rich rhetoric in KA [17,82]. Helpful and insightful answers often get more up-votes, contributing to reputation-based online leadership [4,81]. By contrast, the audience may not value lexical diversity in KS since diversity often means divergent opinions and modification requests, creating more tensions. This is because the topic under discussion in KS is often narrowed, concentrating on specific details of the original answer [28]. Diversified ideas and multiple perspectives are less likely to be welcomed because knowledge shapers often attempt to defend a particular idea. In practice, IT functionality may also limit lexical diversity in KS. For example, in StackExchange, modifications and targeted critiques are posted using the "comment" function, which is much shorter than providing a new post (or reply) in KA. In such a limited space, a less-elaborated idea with high lexical complexity is less likely to be valued by the audience. Thus, we expect lexical diversity to be a better communication style for KA, but not for KS, because diversity may lead to more tensions in KS than in KA [59]. Thus, H2 is proposed as follows:

H2: Lexical diversity of KA has a more positive impact on leadership in online Q&A communities than lexical diversity of KS.

3.3. Positive sentiment and online leadership from KA versus KS

Finally, we consider the role of positive sentiment in affecting the impacts of KA and KS on leadership. The direct impact is also expected to be ambivalent. Previous studies have shown that emotional appeals are effective persuasive vehicles in communication [88,89]. Emotion words or emotional framing of messages are effective stimuli that can elicit more cognitive load and attention [90], thus facilitating perceptual fluency and generating influence on message recipients. Many studies have reported significant impacts of positive sentiment on the effectiveness of online information dissemination [91–93]. For example, expressions related to gratitude and reciprocity are positively associated with the success of influential members in online communities [94]. Members who use more positive sentiment in online Q&A communities are more likely to establish affective bridges with other members and gain recognition [4]. As such, both KA and KS behaviors can benefit from a positive sentiment. On the other hand, sentiment used in online posts may hinder the objectiveness and rationality of the writer [95], resulting in communication inefficiency. Sentiment polarity (e.g., extreme positive sentiment) may lead to unfavorable judgments, such as untrustworthiness and skewness [76,96], leading to negative evaluation toward the post writer [76].

Like the other two linguistic complexity dimensions, audiences for KA and KS may value positive sentiment differently. Knowledge contributors who receive critiques and comments from knowledge shapers may experience more conflicts and tension because people tend to hold on to their opinions and are reluctant to change the posted information [59]. Such tensions are less salient in KA when members answer new questions since they do not need to defend themselves against some existing posts. Consequently, positive sentiment is more likely to be valued in KS than in KA as it can be used as a lubricant for knowledge shapers to reconcile the conflicts and create affective bridges [4]. In addition, emotional regulation is a common strategy to buffer inter-group conflicts [97,98], which could be applied to regulate conflicts and tensions of KS in online Q&A communities. Knowledge shapers may apply the positive sentiment to establish affective bridges with knowledge adders to ensure successful knowledge exchange and integration. Although knowledge adders may also use positive sentiment to attract and persuade the audience, this affective bridge is less important considering the limited tensions and conflict within KA. Furthermore, the threats associated with the positive sentiment (i.e., hinder objectivity and rationality) would exert more negative influence in KA than in KS. Prior research [11] suggests that objectivity is a desirable attribute

Fig. 3. Example of KA versus KS behavior
(Source: https://gamedev.stackexchange.com/questions/190038/place-buildings-to-represent-village)

for KA, resulting in the perception of enhanced quality. As such, the objectivity bias associated with positive sentiment may pose more threats to KA than to KS. Thus, we expect that positive sentiment plays a more important role in promoting leadership through KS than in KA. We hypothesize the following:

H3: Positive sentiment of KS has a more positive impact on leadership in online Q&A communities than the positive sentiment of KA.

4. Methodology

4.1. Research setting and data collection

To test our hypotheses, we collect data from StackExchange.com, a large online Q&A community that rely on voluntary user participation [99]. Originated from Stack Overflow, a successful Q&A website for programmers, StackExchange is a fast-growing platform. By February 2022, it has built more than 173 communities specialized in various topics [100], from software programming to cooking, photography, and gaming. We chose StackExchange because it is a representative online Q&A community and has been widely adopted in previous online community research [3,101].

StackExchange adopts a reputation-based leadership system that relies on members' participation and recognition. Members obtain reputation scores when the post (i.e., a question post or an answer post) is voted up or the answer is accepted. Low-quality questions and answers will be punished by taking away the reputation scores. Commenting does not receive reputation scores directly but is greatly encouraged by the platform. In this study, we consider an answer post as a representation of KA behavior while commenting as a representation of KS behavior. An example of the comment and answer function is presented in Fig. 3, and the analysis procedure is presented in Fig. 4.

Previous studies [4,17] suggested that science and technology is one of the most popular topics in online Q&A communities. We randomly selected two sites within StackExchange (i.e., Game development versus Security) that are (1) within the scope of science and technology, (2) active and popular, (3) similar in size (i.e., number of members), and (4) similar in site age, as shown in Table 3. Although these two sites do not receive as much traffic as those mega-sites like "Super User", they are indeed representative. These selection criteria help us control some site-level impacts such as member tenure, activeness, and overall

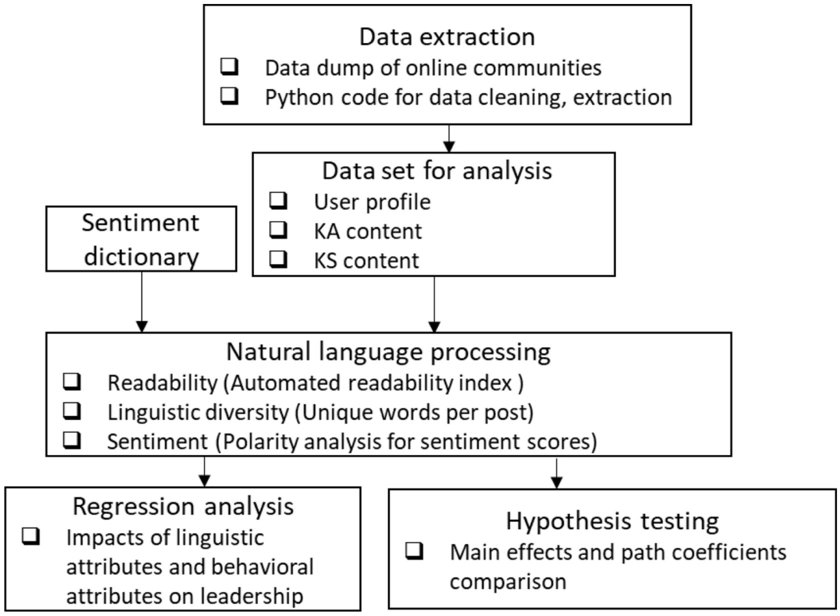

Fig. 4. Analytical process

Table 3
Online community descriptive statistics

Site	Game development	Security
Tagline	Q&A site for professional and independent game developers	Q&A site for security professionals
Collection URL	https://gamedev.stackexchange.com/	https://security.stackexchange.com/
Inception	September, 2010	November, 2010
Members	12,394	19,138
Posts	283,202	416,634

participation level. Table 3 shows details of the two communities used in this study. Data were collected through StackExchange's online data dump [2] with the period between September 2010 and March 2021. There are a total of 699,836 answers and comments posted by 31,532 unique users.

4.2. Measures

Following previous research, **online leadership** is measured by the member's total reputation score [102–104]. The two sites independently assign reputation scores to their members, so if a member participates in both sites, two total reputation scores will be given. In our sample, we did not find individuals participating in both game development and security communities potentially because of the different foci of these two communities. We limited our sample to members who have at least 50 reputation scores[3] since users cannot post comments below this threshold score [105]. We rescale the reputation score by the member's total number of KA to control the potential direct effect of overall participation on leadership (i.e., if a member participates more, he has more chances to get up-votes and earn a higher reputation score).

KA is measured by a member's total number of posts that aim to answer unresolved questions. These KA posts were identified in the "Posts" file in the data dump. The StackExchange platform automatically checks whether newly posted questions have relevance with any old questions to ensure the novelty of newly added knowledge in the platform. Thus, we expect that answering a question is a valid proxy for KA behaviors that focus on adding knowledge to the existing repository.

KS is measured by a member's total number of comments. Unlike an answer post that directly replies to the original question for open discussion, comments are more like a "post-it" attached to an answer or a question post. They are shown in the context of the original post. Technically, an answer post (i.e., KA) uses the reply function and has a permanent link, whereas a comment post uses the comment function and does not have its own link. These KS posts were identified in the "Comments" file in the data dump. The main purpose of comments is to offer feedback and modification suggestions for the already posted answers, thus being a good proxy for KS behaviors that emphasize shaping existing knowledge.

Readability is measured as the average automated readability index (ARI) of members' posted messages. ARI is endorsed in previous studies [4] because it considers both the lengths of characters in a word and the length of words in a sentence, which can better mitigate bias due to text length [106]. It also gives a more accurate estimation compared to the readability index relying on syllables [65]. For each member, we calculate the average readability scores for KA and KS posts separately in Python. The higher the ARI score, the less is the readability of the text (see eq.1).

$$ARI = 4.71 * \left(\frac{\#\ Characters}{\#\ Words}\right) + 0.5 * \left(\frac{\#\ Words}{\#\ Sentences}\right) - 21.43 \tag{1}$$

Lexical diversity is measured as unique words per post as did in previous studies [4]. First, using a Python dictionary (a Python build-in method), we create a word dictionary for each member that contains no redundancy words based on his/her posts. Each row in the dictionary contains the unique words that a member has used in one message. The lexical diversity was computed based on each member's average length of the rows in the dictionary, which corresponds to the average number of unique items stored in the data structure of dictionaries. KA versus KS posts are calculated separately.

The **sentiment score** of each post is calculated using Natural Language Toolkit, a Python library that contains sentiment analysis and opinion mining algorithms [107–109]. The sentiment analysis algorithm identifies positive words based on the AFINN, a word-based classifier that provides emotional scores for a large set of Internet languages [110]. The positive sentiment score was identified as the percentage of

[2] Stack Exchange data dump: https://archive.org/download/stackexchange
[3] There is no maximum score limit at StackExchange, while the minimum reputation score is 0.

positive words in a posted message [70]. The final positivity score ranges from 0 to 1. Since we conduct member-level analysis, we calculate the average sentiment scores for each member based on his/her KA versus KS posts.

We control for factors related to member participation and popularity, which are often theorized as antecedents of online leadership in previous research. First, previous studies have suggested that **tenure** (i.e., the total number of years stayed in the community) is an important determinant for online leadership [21] because those who stay longer in the communities may participate more. Similarly, we controlled for overall participation [4]. KA participation is inherently controlled since the dependent variable (i.e., reputation score) is rescaled by each member's total number of KA posts. Hence, we model **KS participation** (i.e., the total number of KS posts) separately as a control variable. In addition, participation may be awarded by badges, which need to be controlled as well. The **number of badges** represents the extent of awards given by the system based on members' constructive activities in online Q&A communities [99], which is measured by the total number of badges a member has been awarded. Badges could motivate members to enhance their recognition and leadership in online Q&A communities [99,111].

For member popularity, we control two factors. First, **personal profile exposure** refers to the extent of a member's exposure of personal profiles in the online Q&A community to other community members [112,113] and is measured as a member's total number of profile views. Online leadership may be enhanced through network expansion and increased popularity due to more personal profile exposure [112,114]. Second, the **audience size** is measured as the total number of views in all the posts a member has contributed [115,116]. Online leadership may be enhanced by exposing a members' contribution to more audiences in the online Q&A communities [117,118].

Although various individual characteristics can be added to the model, we focus on those that are most likely to have significant impacts on the dependent variable or serve as confounding factors. It should be noted that the secondary data source used for this investigation does not include user demographic information such as age, gender, and race due to the platform's data collection and disclosure policy. However, these personal identity characteristics should not significantly influence our dependent variable or serve as confounding factors since reputation scores are determined by community members' answers/posts, and identifying characteristics of members who vote on posts are not visible to the community. It is also worth noting that the data source used in this study covers the entire population of the sub-communities of interest. Thus, demographic-based sampling bias would not be present in our analysis.

Table 4
Descriptive statistics (N = 31,532)

Panel A: Original values				
Variable	Mean	Std. dev.	Min.	Max.
Online leadership	450.23	3,143.07	50	310,121
Readability of KA	26.80	17.64	3.35	1,183.45
Readability of KS	13.35	6.30	0.02	252.75
Lexical diversity of KA	97.39	51.14	7	927
Lexical diversity of KS	28.93	13.64	2.0	91.0
Sentiment of KA	0.53	0.55	0	1
Sentiment of KS	0.54	0.77	0	1
Tenure	4.44	2.86	0	10.63
KS participation	14.82	133.61	1	13,930
Personal profile exposure	43.20	437.78	0	50,773
Number of badges	9.06	21.97	1	1,734
Audience size	35,173.65	237,240.32	7	23,522,204
Panel B: Rescaled values				
Variable	**Mean**	**Std. dev.**	**Min.**	**Max.**
Rescaled online leadership	101.68	120.97	3	7691
Log (readability of KA)	1.38	0.19	0.53	3.07
Log (readability of KS)	1.10	0.16	-1.76	2.40
Log (lexical diversity of KA)	1.93	0.21	0.85	2.97
Log (lexical diversity of KS)	1.41	0.22	0.30	1.96
Log (KS participation)	0.59	0.53	0	4.14
Log[a] (personal profile exposure)	0.93	0.64	0	4.71
Log (number of badges)	0.76	0.37	0	3.24
Log (audience size)	3.60	0.92	0.85	7.37

Since the variable of personal profile exposure contains 0, a constant of 1 is added to the variable to ensure the validity of log transformation, as suggested in recent statistics research [128].

4.3. Analytical approach

Our dependent variable is a count of the member's reputation score. Traditional OLS-based regression models are biased and inconsistent when the dependent variable is measured as a count [21] because overdispersion may bias the estimation. Our dataset exhibits such overdispersion as evidenced by the fact that the variance of the dependent variable is substantially larger than its mean. Following the recommendations of previous studies, we apply negative binomial models to test our model using SPSS ver 28 [21,46].

We follow a two-step procedure to test our hypotheses. First, we estimate the impacts of linguistic complexity for KA versus KS on online leadership using negative binomial regression, with the following model specifications (see eq.2 and eq.3).

$$Reputation = \beta_0 + \beta_1\ Tenure + \beta_2\ KS\ Participation + \beta_3\ Network\ Exposure\ + \beta_4\ Badges + \beta_5\ Audience\ size + \beta_6\ Readability_{KA} + \beta_7\ Lexical\ diversity_{KA} + \beta_8\ Sentiment_{KA} + \varepsilon \quad (2)$$

$$Reputation = \beta_0 + \beta_1\ Tenure + \beta_2\ KS\ Participation + \beta_3\ Network\ Exposure\ + \beta_4\ Badges + \beta_5\ Audience\ size + \beta_6\ Readability_{KS} + \beta_7\ Lexical\ diversity_{KS} + \beta_8\ Sentiment_{KS} + \varepsilon \quad (3)$$

where β_0 represents the constant, β_1 to β_8 represent the coefficients, and ε represents the error term. Subscripts KS and KA indicate a member's total KA versus KS contributions.

Next, we compare the relative importance of the impacts in step 1 as

Table 5
Inter-correlations of variables (N = 31,532)

	Variables	1	2	3	4	5	6	7	8	9	10	11	12
1	Online leadership (rescaled)	1											
2	Log (readability of KA)	-.014*	1										
3	Log (readability of KS)	.025**	.127**	1									
4	Log (lexical diversity of KA)	.067**	.332**	.120**	1								
5	Log (lexical diversity of KS)	.019**	.017**	.348**	.291**	1							
6	Sentiment of KA	.011	-.055**	.033**	.018**	.044**	1						
7	Sentiment of KS	.039**	-.017**	-.044**	.030**	.023**	.062**	1					
8	Tenure	.045**	.007	.062**	.007	-.004	.023**	-.007	1				
9	Log (KS participation)	-.154**	.021**	.069**	.103**	.079**	.000	-.112**	.261**	1			
10	Log (personal profile exposure)	.090**	-.056**	.056**	-.018**	.007	.018**	-.061**	.359**	.643**	1		
11	Log (number of badges)	.065**	.005	.038**	.026**	-.010	-.010	-.049**	.364**	.677**	.762**	1	
12	Log (audience size)	.032**	-.047**	.081**	-.029**	.045**	.029**	-.063**	.320**	.537**	.734**	.715**	1

Note: * $p < 0.05$; ** $p < 0.01$

Table 6
Negative binomial regression results

Variable	Model 1 (Control)	Model 2 (Main effects of KA)	Model 3 (Main effects of KS)
Tenure	0.017 ** (0.002)	0.017 ** (0.002)	0.016** (0.002)
Log (KS participation)	-0.824** (0.014)	-0.870** (0.015)	-0.845 ** (0.015)
Log (personal profile exposure)	0.363 ** (0.015)	0.372 ** (0.015)	0.368 ** (0.015)
Log (number of badges)	0.513 ** (0.027)	0.503 ** (0.027)	0.534 ** (0.027)
Log (audience size)	-0.126 ** (0.010)	-0.120 ** (0.010)	-0.135 ** (0.010)
Log (readability of KA)		0.229 ** (0.031)	
Log (lexical diversity of KA)		0.597 ** (0.027)	
Sentiment of KA		0.084 (0.047)	
Log (readability of KS)			-0.190 ** (0.038)
Log (lexical diversity of KS)			0.244 ** (0.027)
Sentiment of KS			0.081 * (0.038)
Constant	4.702 ** (0.026)	3. 853** (0.062)	4.165 ** (0.051)
Log-likelihood	-173, 755	-173,508	-173,678
AIC	347,522	347,034	347,374
BIC	347,572	347,109	347,458

Note: * $p < 0.05$; ** $p < 0.01$; standard errors of coefficients are in parentheses.

the proxy for the fit. The comparison is calculated using the formula of path coefficient comparison (see eq.4) [119,120]. In short, we compare the impacts of linguistic complexity on online leadership for the same sample under KA and KS using path coefficient comparison [120]. The fit between linguistic complexity and KA is detected when the coefficients are larger than those of KS or structurally different than those of KS (e.g., significant versus insignificant coefficients). Fit and non-fit are comparative in nature, suggesting that one specific linguistic style is more appropriate for KA than KS, or vice versa.

$$t = \frac{Path\ coefficient\ 1 - Path\ coefficient 2}{\left[\sqrt{\frac{(m_{-1})^2}{(m+1-2)} * \left(SE_1^2 + SE_2^2\right)}\ \right] * \left[\sqrt{\frac{1}{m} + \frac{1}{n}}\right]} \tag{4}$$

Note: Path coefficient 1 and SE 1 refer to the coefficient and its standard error in the KA group; Path coefficient 2 and SE 2 refer to the coefficient and its standard error in the KS group; m and n are the sample size in the KA group and KS group, respectively.

Table 7
Summary of findings

Hypotheses	Path coefficient of KA	Path coefficient of KS	Diff.	Sig.	Result
H1: The readability of KA has a more positive impact on leadership in online Q&A communities than the readability of KS. $\beta_{RKA \to LD} > \beta_{RKS \to LD}$	0.229 ** (0.031)	-0.190 ** (0.038)	0.419 structurally different	**	Supported
H2: Lexical diversity of KA has a more positive impact on leadership in online Q&A communities than lexical diversity of KS. $\beta_{LKA \to LD} > \beta_{LKS \to LD}$	0.597 ** (0.027)	0.244 ** (0.027)	0.353	**	Supported
H3: Positive sentiment of KS has a more positive impact on leadership in online Q&A communities than the positive sentiment of KA. $\beta_{SKA \to LD} < \beta_{SKS \to LD}$	0.084 (0.047)	0.081 * (0.038)	Structurally different	-	Supported

Note. * $p < 0.05$; ** $p<0.01$

5. Results

5.1. Descriptive results

Table 4 presents the descriptive statistics. To mitigate the estimation bias, we take the log transformation of readability, lexical diversity, and KS participation so that they are similar in their scales (see Panel B). Table 5 presents the correlations, which suggest that all variables of

Table 8
Summary of robustness check

Test description	Objective	Results
Test 1 – Different readability calculation	Alternative proxy test	Table A. 1-2. Robustness supported
Test 2 – Different lexical diversity calculation (MTLD)	Alternative proxy test	Table A. 3-4. Robustness supported
Test 3 – Different DV	Alternative proxy test	Table A. 5-6. Robustness supported
Test 4 – Garen's approach for endogeneity test	Endogeneity error test	Table A. 7. Robustness supported
Test 5 – Split sample test	Split sample robustness	Table A. 9-12 Robustness supported

interest are statistically different. Although correlations among personal profile exposure, number of badges, and audience size are relatively high, the variance inflation factors (VIFs) of these variables did not exceed 3.3 (see Table A8 in the Appendix), indicating that multicollinearity did not pose a threat to the validity of our results [121,122].

5.2. Hypotheses testing

Table 6 shows the results of our hypotheses testing using a stepwise approach. Model 1 shows the impacts of control variables, Model 2 shows the main effects of linguistic complexity for KA, and Model 3 presents the main effects of linguistic complexity for KS. Overall, the binomial regression model suggests better goodness-of-fit after adding the linguistic features in models 2 and 3, as indicated by higher log-likelihood and lower AIC and BIC values.

Table 7 summarizes the findings and compares the relative importance of the linguistic impacts under KA versus KS. The readability of KA has a significantly stronger impact on online leadership than the readability of KS (β_{KA} - β_{KS} = 0.419, $p < 0.05$), thus supporting hypothesis 1. In addition, whereas the readability of KA has a positive impact, the readability of KS seems to negatively influence online leadership, indicating more fit between readability and KA than that between readability and KS. A potential explanation is that comments are relatively short; simple sentence structure and short expressions (i.e., high readability score) are more likely to create a "lack of effort" impression and thus is less valued by the audience [105]. The lexical diversity of both KA and KS has positive impacts, but the lexical diversity of KA has a stronger impact than that of KS (β_{KA} - β_{KS} = 0.353, $p < 0.05$), thus supporting hypothesis 2 and suggesting more fit between lexical diversity and KA than that between lexical diversity and KS. Finally, the sentiment of KS has a stronger positive impact on online leadership than the sentiment of KA (β_{KS} $p < 0.05$ versus β_{KA} non-significant), thus supporting hypothesis 3 and suggesting more fit between sentiment and KS than that between sentiment and KA. Since KA behaviors involve little conflict between knowledge seekers and knowledge contributors, using positive language to mitigate conflicts is less of a concern.

5.3. Robustness check

The estimation of our cross-sectional model may be biased due to measurement and endogeneity issues. Thus, we conducted several robustness tests. Table 8 summarizes the tests we have conducted, and the detailed results can be found in our Appendix.

First, we apply alternative measures for the independent variables. We first replace the readability measure with the Gunning–Fog Readability Index [23]. Results are qualitatively unchanged (see Tables A1 and A2 in the Appendix).

Next, lexical diversity is replaced with the measure of textual lexical diversity (MTLD) [81]. MTLD is calculated as the mean length of sequential word strings in a text that maintains a given type-token ratio value (e.g., 0.720), which can be computed by the number of unique words divided by the total number of words. This threshold of type-token ratio allows for a control for the error introduced by text length. When text length increases and the type-token ratio naturally decreases to the threshold of 0.720, it will generate a new string for further calculation. With the measure of MTLD, the hypothesis testing results also remained unchanged (see Tables A3 and A4 in the Appendix).

We also conducted a robustness test using an alternative dependent variable – the total reputation score. This is different from our current measure, which takes into account the number of KA posts. It is an alternative measure for leadership as it represents the overall reputation accumulated in the online community. We applied this post score as an alternative DV, and the hypothesis testing results remained consistent (see Tables A5 and A6 in the Appendix).

In our study, linguistic complexity may be endogenous in our model in two ways: (1) we may not have accounted for all unobserved heterogeneity associated with linguistic diversity, and (2) reverse causation may be present as leadership may impact their expression style. We applied Garen's approach [123] to test endogeneity concerning lexical diversity. We identified the overall lexical capability of a member as the instrumental variable for lexical diversity. The lexical capability is calculated based on the total number of unique words from a member's all previous posts divided by the total number of posts [4]. As such, when calculating lexical capability, the python dictionary for unique words is calculated based on all posts by a community member. By contrast, when calculating lexical diversity of language, the python dictionary is calculated based on every single post by a community member. Prior research on lexical diversity suggests that a person's capability to use rich language influences the language used in each post [17]. On the other hand, the overall lexical capability is not directly correlated with reputation scores, as community members gain reputation scores through accumulated up-votes and answer acceptance. Our conclusions about the role of lexical diversity in explaining leadership hold true after controlling for the endogeneity of overall lexical diversity (see Table A7 in the Appendix).

Lastly, we performed a split sample analysis and tested our hypotheses using the sample from the Game StackExchange community and the Security StackExchange community separately. The results are consistent across these two communities (see Tables A9 and A10 for the Game StackExchange community and Tables A11 and A12 for the Security StackExchange community).

6. Discussion

This study investigates how knowledge contributors' accommodation of linguistic complexity (i.e., readability, lexical diversity, and sentiment) contributes to reputation-based leadership in the online Q&A community under two types of knowledge contribution behaviors: KA (answering questions and thus targeting knowledge seekers) and KS (commenting and thus targeting other knowledge contributors). Using data from the StackExchange online Q&A community, we found that the readability and lexical diversity of KA have more substantial associations with online leadership than those of KS. However, the sentiment of KS has a stronger impact than the sentiment of KA. These linguistic factors play an essential role in strengthening the designated roles of KA and KS. For instance, readability may strengthen the comprehensibility of KA; lexical diversity may strengthen the credibility and trustworthiness of KA, and sentiment may buffer the potential conflicts raised by KS. This suggests that linguistic features have differentiated impacts on leadership in online Q&A communities depending on the types of knowledge contribution to be communicated.

6.1. Implications for research and practice

Extant research shows that online leadership plays an important role in sustaining online communities [5]. For online Q&A communities, member leadership is particularly important to motivate community engagement and facilitate high-quality knowledge exchange [12,22]. Extensive research in the fields of communication and leadership emphasizes that, in addition to what is communicated, how a message is communicated to its audience is an important determinant of its effectiveness [33,34]. In the context of online communities, the literature has explored knowledge contribution (what is being communicated) and linguistic elements (how it is being communicated); however, findings remain ambiguous and conflicting on how linguistic aspects of knowledge contribution influence online leadership [4,17,23,24]. We posit that these ambiguous and conflicting findings are due to a lack of focus and granularity on the type of knowledge being contributed. This study provides academics and practitioners with a clearer understanding of leadership formation in online Q&A communities by differentiating between different types of knowledge contribution (KA and KS) and illustrating that linguistic elements of communication (readability, lexical diversity, and sentiment) should be attuned to the distinct audiences of different knowledge contribution types.

The study contributes to the literature in several ways. First, we contribute to the online leadership literature by taking a richer perspective of knowledge contribution behaviors. Differentiating KA and KS behaviors allows us to gain deeper insights into the impacts of distinctive linguistic styles in online Q&A communities by delineating their main audiences, the target audience's level of expertise, and potential tensions. Our results suggest that avoiding a one-fits-for-all communication strategy is beneficial for gaining reputation-based leadership in online Q&A communities. Being aware of such nuances allows members to engage in knowledge exchange activities more effectively. Although existing studies [4,17] have suggested the importance of both contribution behaviors and linguistic complexity to online leadership, the findings of this study add to the existing research by highlighting the importance of adjusting linguistic styles based on types of contribution behaviors (i.e., KA and KS) to earn leadership.

Second, our study takes an integrative perspective of knowledge contribution and linguistic features and therefore advances our knowledge regarding the relative importance of linguistic complexity for different knowledge contribution behaviors. This approach extends previous online leadership studies that focused on overall linguistic impacts by considering the various types of audiences [4,17]. Thus, this investigation offers a more fine-grained evaluation of the linguistic impacts on online leadership. Our study provides implications for the management of knowledge contribution literature by showing the importance of accommodated linguistic style in knowledge contributions.

Our study also extends the application of the communication accommodation perspective to leadership research in the online Q&A communities. Previous studies [124,125] based on CAT mainly examined communication styles in organizational contexts with formal organizational structure, with an exception of applying this theory in user communities of tools and products [56]. Our study shows that in online Q&A communities where people in geographically diverse areas exchange knowledge, communication accommodation is still an effective strategy to increase one's reputation-based leadership. As such, CAT has been extended to textual-based and asynchronous communication in online Q&A communities, a novel context different from the original context of the theory.

Our results can also inform online leaders and community managers. Firstly, by comparing KA and KS contribution behaviors, we provide implications on how leaders can leverage their linguistic style to earn better recognition by bearing different types of audiences in mind with varying knowledge contribution behaviors. For KA that targets knowledge seekers, online leaders should post in highly readable and lexically diverse language. This is because KA is often communicated to knowledge seekers who have limited knowledge on certain topics and thus need readable and easy-to-understand information. At the same time, lexically diverse language may facilitate knowledge seekers to understand a topic from multiple perspectives, thus deepening their overall understanding. By contrast, online leaders should post in lexically diverse and positive language for KS that targets other knowledge contributors. This is because KS is often targeted at knowledge adders who already have an adequate understanding of a topic and may be reluctant to modify their contribution. Applying positive language may serve as a buffer to avoid potential conflict and facilitate information exchange. By accommodating linguistic style based on the type of contribution behaviors (i.e., KA and KS), online leaders may gain further recognition and reputation from the community.

Secondly, for those who manage or sponsor online Q&A communities, the findings highlight linguistic patterns as an important yet often neglected area in online content management. Since tailoring linguistic characteristics to the type of knowledge contribution (KA or KS) may improve the effective dissemination of knowledge, enhancing member satisfaction and activeness, community managers can put more effort into managing the content from a linguistic perspective. Some online communities have rules regarding using friendly and polite expressions. However, there is limited systematic monitoring and management of linguistic patterns in these online communities.

6.2. Limitations and future research directions

The study has several limitations, which also serve as opportunities for future research. First, our dataset only contains cross-sectional reputation scores, limiting our understanding of the emergence of online leadership over time. More research is warranted to identify the time dynamics of communication accommodation patterns of online leaders. For example, future research may reconstruct users' reputation in StackExchange at a specific time period and further examine the variation of reputation.

Second, our results support the important role of accommodated communication (e.g., accommodated linguistic complexity depending on KA or KS). However, individuals' linguistic styles may be chronological, depending on one's personality, education, experience, and other identity-related factors [82,126]. Thus, to what extent the linguistic complexity is driven by an online leader's attributes other than the targeted audience is largely unknown. We were not able to control for members' demographic and identity-related factors due to the nature of our dataset and the platform's data collection and disclosure policies. However, we do not expect these factors to influence our results since identity characteristics of members who vote on posts are not visible to the community. Additionally, since the data source used covered the entire population in the sub-communities investigated, there would be no demographic-based sampling bias in our analysis. Our robustness checks also confirm our estimation. While these individual differences are outside the scope of our investigation, we acknowledge their potential influence on online community leadership could be an interesting avenue for future research.

Third, our findings are based on online Q&A communities with topics related to science and technology, which may have unique conventions on the type of language to use. The linguistic style in communities that focus more on interpersonal and sociopolitical topics may have very different linguistic characteristics; hence, the influence on online leadership may be different. Thus, our results may not be generalizable to communities outside the science and technology context. Nevertheless, we expect that the three dimensions we investigated (i.e., readability, lexical diversity, and sentiment) will remain relevant regardless of the community theme, and future research can investigate other linguistic characteristics that are more relevant to other discussion domains or topics. For example, language politeness has been shown to influence quality perception and assessment of posts in online communities [127], which may influence leadership status.

Fourth, technical characteristics of the platform may limit members' communication accommodation. For instance, comments are often shorter than replies due to the platform's word limitation rather than members' free will. Hence, members may be restricted in adapting their linguistic components freely based on the type of knowledge contribution, which may bias our estimation. While word limitation is of less concern since the computation of readability, lexical diversity, and sentiment are normalized by text length, other technological constraints should be investigated in future research.

Lastly, our KA and KS measures are based on the post labels (i.e., reply post versus comment) in the data dump rather than content analysis, which may introduce measurement error. For instance, the key function of reply versus commenting may not be entirely clear to all members. Some members may use the reply function (KA) instead of commenting function (KS) to provide critiques and comments or use KS to provide supporting arguments. Without a detailed content analysis of each post, some KS posts may be misclassified as KA posts by the data dump. Future research can perform content analysis to understand the topic of KA and KS. For example, topic modeling can be performed to measure posts that provide supportive information versus critiques, which is one of the underlying mechanisms we theorized (i.e., KS involves more critiques and thus may bring tensions) but did not test.

7. Conclusion

This study integrates the behavioral and linguistic perspectives of online leadership and examines how three dimensions of linguistic complexity (i.e., readability, lexical diversity, and sentiment) may influence online leadership differently depending on the type of knowledge contribution that is targeted at different audiences (i.e., KA versus KS). By drawing on CAT, we posit that knowledge seekers and contributors have different levels of expertise and online community participation goals, influencing how they evaluate other members' knowledge contributions. Hence, leaders need to accommodate their linguistic styles to achieve better communication efficiency and reputation-based recognition to guarantee and further their leadership status. Our findings suggest that online leaders should use more readable and lexically diverse language in KA contributions while using more positive emotion in KS contributions.

CRediT author statement

Xuecong Lu: Conceptualization, Methodology, Formal Analysis, Writing – Original Draft; **Jinglu Jiang:** Conceptualization, Formal Analysis, Writing – Original Draft; **Milena Head:** Supervision, Conceptualization, Writing – Review & Editing, Funding Acquisition; **Junyi Yang:** Formal Analysis, Writing – Review & Editing.

Declaration of interests

There is no declaration of interests from all authors.

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Appendix

Tables A1–A12.

Table A1
Negative binomial regression results with Gunning–Fog Readability Index as an alternative measure for readability

Variable	Model 1 (Control)	Model 2(Main effects of KA)	Model 3(Main effects of KS)
Tenure	0.017 ** (0.002)	0.017 ** (0.002)	0.016 ** (0.002)
Log (KS participation)	-0.824** (0.014)	-0.872** (0.015)	-0.841** (0.015)
Log (personal profile exposure)	0.363 ** (0.015)	0.371 ** (0.015)	0.368 ** (0.015)
Log (number of badges)	0.513 ** (0.027)	0.501 ** (0.027)	0.534 ** (0.027)
Log (audience size)	-0.126 ** (0.010)	-0.118 ** (0.010)	-0.135 ** (0.010)
Log (readability of KA)		0.565 * (0.063)	
Log (lexical diversity of KA)		0.591 ** (0.026)	
Sentiment of KA		0.077 (0.047)	
Log (readability of KS)			-0.354 ** (0.086)
Log (lexical diversity of KS)			0.283** (0.026)
Sentiment of KS			0.076* (0.038)
Constant	4.702 ** (0.026)	4.586 ** (0.118)	3.692 ** (0.154)
Log-likelihood	-173, 755	-173,606	-173,691
AIC	347,522	347,231	347,426
BIC	347,572	347,307	347,501

Note: * $p < 0.05$; ** $p < 0.01$

Table A2
Hypothesis test with Gunning–Fog Readability Index as an alternative measure for readability

Hypotheses	Path coefficient of KA	Path coefficient of KS	Diff.	Sig.	Result
H1: The readability of KA has a more positive impact on leadership in online Q&A communities than the readability of KS. $\beta_{RKA \to LD} > \beta_{RKS \to LD}$	0.565 * (0.063)	-0.354 ** (0.086)	0.919	**	Supported
H2: Lexical diversity of KA has a more positive impact on leadership in online Q&A communities than lexical diversity of KS. $\beta_{LKA \to LD} > \beta_{LKS \to LD}$	0.591 ** (0.026)	0.283** (0.026)	0.308	**	Supported
H3: Positive sentiment of KS has a more positive impact on	0.077 (0.047)	0.076* (0.038)	Structurally different	-	Supported

(continued on next page)

Table A2 (*continued*)

Hypotheses	Path coefficient of KA	Path coefficient of KS	Diff.	Sig.	Result
leadership in online Q&A communities than the positive sentiment of KA. $\beta_{SKA \rightarrow LD} < \beta_{SKS \rightarrow LD}$					

Table A3
Negative binomial regression results with the MTLD is an alternative measure for lexical diversity

Variable	Model 1 (Control)	Model 2 (Main effects of KA)	Model 3 (Main effects of KS)
Tenure	0.017 ** (0.002)	0.016 ** (0.002)	0.016 ** (0.002)
Log (KS participation)	-0.824** (0.014)	-0.866** (0.015)	-0.846** (0.015)
Log (personal profile exposure)	0.363 ** (0.015)	0.365 ** (0.015)	0.367 ** (0.015)
Log (number of badges)	0.513 ** (0.027)	0.504 ** (0.027)	0.533 ** (0.027)
Log (audience size)	-0.126 ** (0.010)	-0.121 ** (0.010)	-0.135 ** (0.010)
Log (readability of KA)		0.132 ** (0.030)	
Log (lexical diversity of KA)		1.562 ** (0.066)	
Sentiment of KA		0.046 (0.047)	
Log (readability of KS)			-0.181 ** (0.038)
Log (lexical diversity of KS)			0.595** (0.063)
Sentiment of KS			0.076* (0.038)
Constant	4.702 ** (0.026)	3.563 ** (0.068)	4.123** (0.052)
Log-likelihood	-173, 755	-173,477	-173,672
AIC	347,522	346,973	347,362
BIC	347,572	347,048	347,437

Note: * $p < 0.05$; ** $p < 0.01$

Table A4
Hypothesis test with the MTLD is an alternative measure for lexical diversity

Hypotheses	Path coefficient of KA	Path coefficient of KS	Diff.	Sig.	Result
H1: The readability of KA has a more positive impact on leadership in online Q&A communities than the readability of KS. $\beta_{RKA \rightarrow LD} > \beta_{RKS \rightarrow LD}$	0.132 ** (0.030)	-0.181 ** (0.038)	0.313	**	Supported
H2: Lexical diversity of KA has a more positive impact on leadership in online Q&A communities than lexical diversity of KS. $\beta_{LKA \rightarrow LD} > \beta_{LKS \rightarrow LD}$	1.562 ** (0.066)	0.595** (0.063)	0.967	**	Supported
H3: Positive sentiment of KS has a more positive impact on leadership in online Q&A communities than the positive sentiment of KA. $\beta_{SKA \rightarrow LD} < \beta_{SKS \rightarrow LD}$	0.046 (0.047)	0.076* (0.038)	Structurally different	-	Supported

Table A5
Negative binomial regression results with a member's total reputation score as dependent variable

Variable	Model 1 (Control)	Model 2(Main effects of KA)	Model 3(Main effects of KS)
Tenure	0.018 ** (0.002)	0.018 ** (0.002)	0.018 ** (0.002)
Log (KS participation)	0.144** (0.017)	0.122** (0.017)	0.138** (0.017)
Log (KA participation)	0.181 ** (0.022)	0.204 ** (0.022)	0.186 ** (0.022)
Log (personal profile exposure)	-0.048 ** (0.011)	-0.048 ** (0.010)	-0.048 ** (0.011)
Log (number of badges)	0.838** (0.021)	0.838** (0.021)	0.843** (0.021)
Log (audience size)	0.312 ** (0.009)	0.308 ** (0.009)	0.308 ** (0.009)
Log (readability of KA)		0.170 ** (0.033)	
Log (lexical diversity of KA)		0.200 ** (0.029)	
Sentiment of KA		0.082 (0.052)	
Log (readability of KS)			-0.116 ** (0.038)
Log (lexical diversity of KS)			0.071* (0.028)
Sentiment of KS			0.083* (0.037)
Constant	4.022 ** (0.030)	3.877 ** (0.067)	3.802** (0.052)
Log-likelihood	-199, 364	-199,333	-199,350
AIC	398,743	398,687	398,720
BIC	398,809	398,770	398,803

Note: * $p < 0.05$; ** $p < 0.01$

Table A6
Hypothesis test with a member's total reputation score as the dependent variable

Hypotheses	Path coefficient of KA	Path coefficient of KS	Diff.	Sig.	Result
H1: The readability of KA has a more positive impact on leadership in online Q&A communities than the readability of KS. $\beta_{RKA\rightarrow LD} > \beta_{RKS\rightarrow LD}$	0.170 ** (0.033)	-0.116 ** (0.038)	0.286	**	Supported
H2: Lexical diversity of KA has a more positive impact on leadership in online Q&A communities than lexical diversity of KS. $\beta_{LKA\rightarrow LD} > \beta_{LKS\rightarrow LD}$	0.200 ** (0.029)	0.071* (0.028)	0.129	**	Supported
H3: Positive sentiment of KS has a more positive impact on leadership in online Q&A communities than the positive sentiment of KA. $\beta_{SKA\rightarrow LD} < \beta_{SKS\rightarrow LD}$	0.082 (0.052)	0.083* (0.037)	Structurally different	-	Supported

Table A7
Two-step endogeneity test

Variable	Step 1 - KA (OLS)DV = lexical diversity of KA	Step 1 – KS(OLS)DV = lexical diversity of KS	Step 2- KA(negative binomial)DV = leadership	Step 2: KS(negative binomial)DV = leadership
Instrumental variable				
Lexical capability	1.705 **	0.283 **		
Endogenous factor				
Leadership	0.081 **	0.009 **		
Residual			0.006 **	0.004 **
Residual x leadership			0.0001 **	-0.0002**
Variable with endogeneity issue				
Log (lexical diversity of KA)			0.326**	
Log (lexical diversity of KS)				0.237**
Other predictive variables				
Log (readability of KA)	-25.784**		0.115**	
Sentiment of KA	-0.830		0.087	
Log (readability of KS)		-19.424**		-0.192**
Sentiment of KS		1.641*		0.078*
Control variable				
Tenure	0.493 **	-0.044	-0.02**	0.016**
Log (KS participation)	43.376**	6.253**	-0.794*	-0.826**
Log (personal profile exposure)	-6.769**	-0.800**	0.421**	0.356**
Log (number of badges)	-15.666**	-7.751**	0.133**	0.520**
Log (audience size)	-8.604**	0.518**	-0.089**	-0.137**
Constant	-19.584 **	-7.871 **	4.376 **	4.189 **
Log-likelihood	-148,093	-118, 934	-173,218	-173,558
AIC	296,208	237,891	346,458	347,137
BIC	296,299	237,982	346,550	347,229

Table A8
Multicollinearity testing results

Variables	VIF values
Tenure	1.177
Log (KS participation)	2.059
Log (personal profile exposure)	3.135
Log (number of badges)	3.239
Log (audience size)	2.524
Log (readability of KA)	1.165
Log (lexical diversity of KA)	1.260
Sentiment of KA	1.013
Log (readability of KS)	1.170
Log (lexical diversity of KS)	1.261
Sentiment of KS	1.025

Table A9
Negative binomial regression results in the Game StackExchange community

Variable	Model 1 (Control)	Model 2 (Main effects of KA)	Model 3 (Main effects of KS)
Tenure	0.033 ** (0.003)	0.033 ** (0.003)	0.032 ** (0.003)
Log (KS participation)	-0.782** (0.024)	-0.806** (0.024)	-0.790** (0.024)
Log (personal profile exposure)	0.290 ** (0.025)	0.299 ** (0.025)	0.297 ** (0.025)
Log (number of badges)	0.264 ** (0.045)	0.241 ** (0.045)	0.274 ** (0.045)
Log (audience size)	-0.172 ** (0.017)	-0.166 ** (0.017)	-0.180 ** (0.017)
Log (readability of KA)		0.381 ** (0.047)	
Log (lexical diversity of KA)		0.600 ** (0.043)	

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Table A9 (*continued*)

Variable	Model 1 (Control)	Model 2 (Main effects of KA)	Model 3 (Main effects of KS)
Sentiment of KA		-0.008 (0.078)	
Log (readability of KS)			-0.153 * (0.062)
Log (lexical diversity of KS)			0.238 ** (0.044)
Sentiment of KS			0.200 ** (0.059)
Constant	4.792 ** (0.044)	4.158 ** (0.101)	4.299 ** (0.080)
Log-likelihood	-65, 273	-65,167	-65,241
AIC	130,558	130,351	130,500
BIC	130,603	130,418	130,567

Note: * $p < 0.05$; ** $p < 0.01$

Table A10
Hypothesis test with regression results in the Game StackExchange community

Hypotheses	Path coefficient of KA	Path coefficient of KS	Diff.	Sig.	Result
H1: The readability of KA has a more positive impact on leadership in online Q&A communities than the readability of KS. $\beta_{RKA \to LD} > \beta_{RKS \to LD}$	0.381 ** (0.047)	-0.153 * (0.062)	0.534	**	Supported
H2: Lexical diversity of KA has a more positive impact on leadership in online Q&A communities than lexical diversity of KS. $\beta_{LKA \to LD} > \beta_{LKS \to LD}$	0.600 ** (0.043)	0.238 ** (0.044)	0.362	**	Supported
H3: Positive sentiment of KS has a more positive impact on leadership in online Q&A communities than the positive sentiment of KA. $\beta_{SKA \to LD} < \beta_{SKS \to LD}$	-0.008 (0.078)	0.200 ** (0.059)	Structurally different	-	Supported

Table A11
Negative binomial regression results in the Security StackExchange community

Variable	Model 1 (Control)	Model 2 (Main effects of KA)	Model 3 (Main effects of KS)
Tenure	0.017 ** (0.003)	0.017 ** (0.003)	0.017 ** (0.003)
Log (KS participation)	-0.782** (0.018)	-0.831** (0.019)	-0.798** (0.019)
Log (personal profile exposure)	0.334 ** (0.019)	0.345 ** (0.019)	0.338 ** (0.019)
Log (number of badges)	0.657 ** (0.034)	0.645 ** (0.034)	0.674 ** (0.034)
Log (audience size)	-0.115 ** (0.012)	-0.109 ** (0.012)	-0.120 ** (0.012)
Log (readability of KA)		0.050 ** (0.004)	
Log (lexical diversity of KA)		0.530 ** (0.035)	
Sentiment of KA		-0.027 (0.06)	
Log (readability of KS)			-0.023 ** (0.004)
Log (lexical diversity of KS)			0.212 ** (0.035)
Sentiment of KS			0.098 ** (0.004)
Constant	4.674 ** (0.032)	3.697 ** (0.079)	4.317 ** (0.067)
Log-likelihood	-107, 909	-107,783	-107,241
AIC	215,830	215,584	215,788
BIC	215,877	215,655	215,859

Note: * $p < 0.05$; ** $p < 0.01$

Table A12
Hypothesis test with regression results in the Security StackExchange community

Hypotheses	Path coefficient of KA	Path coefficient of KS	Diff.	Sig.	Result
H1: The readability of KA has a more positive impact on leadership in online Q&A communities than the readability of KS. $\beta_{RKA \to LD} > \beta_{RKS \to LD}$	0.050 ** (0.004)	-0.023 ** (0.004)	0.073	**	Supported
H2: Lexical diversity of KA has a more positive impact on leadership in online Q&A communities than lexical diversity of KS.	0.530 ** (0.035)	0.212 ** (0.035)	0.318	**	Supported

(*continued on next page*)

Table A12 (*continued*)

Hypotheses	Path coefficient of KA	Path coefficient of KS	Diff.	Sig.	Result
$\beta_{LKA \to LD} > \beta_{LKS \to LD}$					
H3: Positive sentiment of KS has a more positive impact on leadership in online Q&A communities than the positive sentiment of KA. $\beta_{SKA \to LD} < \beta_{SKS \to LD}$	-0.027 (0.06)	0.098 ** (0.004)	Structurally different	-	Supported

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