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Sustaining online academic discussions: Identifying the characteristics of messages that receive responses

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ABSTRACT

More and more students are learning via online academic discussions, posting messages in an attempt to discuss their learning problems. However, many messages do not receive responses. Posting messages that elicit responses is essential to students' experiences of learning through online discussions, but the characteristics of such messages are seldom studied. To fill this gap, this paper examines the relationship between the characteristics of an online discussion message and its likelihood of receiving a response from others. We conducted the study with a public, online discussion forum about high school-level mathematics—a non-formal learning environment that is not confined to a specific classroom. We randomly sampled 140 topics from the forum and analysed 1,559 reply messages using multilevel logistic regressions at the topic and message level. We found that during an online discussion, a message that either expressed disagreement, included a correct or incorrect idea, or asked a question was more likely to receive a response. Time was another significant predictor; messages posted during the early stage of a discussion or users who responded more promptly were more likely to receive a response. The findings contribute to the understanding of the discourse process and students' learning behaviour in online academic discussions. We propose several recommendations for future research.

1. Introduction

Thanks to advances in technology, students can interact with other students in online communities to seek information or discuss questions (Aloni & Harrington, 2018; De Wever, Schellens, Valcke, & Van Keer, 2006; Woo & Reeves, 2007). There are multiple advantages to online discussions, such as open communication, supportive collaboration, information exchange, and the connection of ideas (Garrison, 2007). It has long been recognised that although learners working together may generate cognitive conflicts (Piaget, 1974), this can enable them to solve problems at a more advanced level than if they worked on the same problems alone (Doise, Mugny, & Perret-Clermont, 1975). For this reason, online discussion forums have been used to support student learning in various educational contexts (e.g., Aloni & Harrington, 2018; Wise & Cui, 2018).

Our research focus is on the characteristics of messages that elicit responses in online academic discussions because they are central to sustaining online discussions and developing online communities (Anderson, 2006; Ridings, Gefen, & Arinze, 2002; Tsai & Pai, 2013). Messages that elicit responses increase the lifespan of a discussion, the participants' sense of belonging, and their engagement in online communities (Lee, Reid, & Kim, 2014; Lewallen, Owen, Bantum, & Stanton, 2014; Tsai & Pai, 2013). They can also reinforce the

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contribution of knowledge to online communities (Jin, Li, Zhong, & Zhai, 2015; Kim & Sundar, 2014; Tausczik & Pennebaker, 2012). In addition, participants can gain a deeper understanding of the learning materials by reviewing and commenting on online messages (Aloni & Harrington, 2018; Cathey, 2007; Tsai & Pai, 2013). It is therefore important to identify those characteristics that affect a message's likelihood of receiving a response in online academic discussion communities.

Past studies have identified various motivational factors that affect online participation and knowledge-sharing behaviours across a range of online communities (e.g., Jin et al., 2015; Joyce & Kraut, 2006; Kim & Sundar, 2014; Wang & Lai, 2006). For example, a survey study by Lee et al. (2014) provided evidence that higher levels of online authors' sense of belonging would lead to higher levels of knowledge-sharing activities. However, we currently know little about the characteristics of a message per se that drive post-replying behaviour in online academic discussion communities.

The present study seeks to understand how students engage other students to respond during online discussions, and how to enhance discussions in online forums. We create a detailed model of actions and sequences across time that affect others' engagement in online discussions, thereby informing current models of motivation and informing online teaching to enhance students' online discussions. Building on past studies that primarily examine post hoc surveys of motivation, this study examines how sequences of students' behaviours affect their likelihood of responding in an online discussion.

We study discussions in an online community forum as a form of non-formal learning. Specifically, we analyse high school students' mathematics discussions from an online public forum that is not attached to any class or school. Examining students' interactions in independent forums not confined to the classroom can improve our understanding of their spontaneous, natural behaviours when responding to one another during online discussions.

2. Research model and hypotheses

For this study, we adopted the theoretical work of cognitive-social theorists, such as Festinger (1957) and Heider (1946), which affirms that cognitive dissonance and imbalance generate a motivational tendency to resolve contradictory cognitions. We also used the theoretical model of helping behaviour as proposed by social psychologists (e.g., Latané & Darley, 1970; Yalom, 2005) to approach the characteristics of messages that elicit responses during online discussions. We developed a research model with hypotheses derived from the literature about online discussions. Based on existing analytical frameworks for online discussion (Chen et al., 2012a; Chen et al., 2012b), our research model was established with five dimensions: (1) evaluations, (2) knowledge content, (3) invitational form, (4) emotional expression, and (5) other characteristics.

2.1. Evaluation

The first dimension—evaluation—concerns whether online authors (or e-authors) expressed agreement, disagreement or gave neutral responses to an e-author's message. According to Rooderkerk and Pauwels (2016), controversial content is a key factor that drives others to react and comment on online messages. Leveraging Festinger's (1957) theory of cognitive dissonance, they maintain that the discovery of dissonance arouses cognitive conflict and initiates peer interaction to reduce such conflict. In this study, consistent with the survey results of Tausczik and Pennebaker (2012), disagreements significantly encouraged participation in an online mathematics community. Therefore, an expression of disagreement is presumably more likely to get a reply (H-1a). In contrast, a study by Joyce and Kraut (2006) suggested that expressing agreement did not influence the probability of whether a message received replies. In the context of an academic discussion, an expression of agreement tends to bring minimal new input for further discussion. Tausczik and Pennebaker (2012) also say that agreeing with comments was not related to participation. Therefore, we hypothesise that messages expressing agreement are less likely to receive replies (H-1b). We thus arrive at the first set of hypotheses.

H-1a. Messages expressing disagreement will increase the likelihood of receiving responses.

H-1b. Messages expressing agreement will decrease the likelihood of receiving responses.

2.2. Knowledge content

The second dimension is the knowledge content of a message. In addition to instances of repetition (repeating ideas that have been mentioned earlier) and non-academic content, a message can be classified as expressing correct or incorrect ideas, or justifications (Chen et al., 2012a; Chen et al., 2012b). Here, justification is an action that supports a new idea by linking it to data using a warrant or backing (Toulmin, 2003). We hypothesise that messages expressing correct ideas (H-2a), incorrect ideas (H-2b) and justifying previous ideas (H-2c) are more likely to receive a reply. These claims are supported by the theoretical work of cognitive-social theorists. Specifically, any new ideas, either correct or incorrect, are likely to create cognitive conflict with other e-authors because respondents may have different conceptualisations of how to approach the problem. Such cognitive conflicts can lead e-authors to respond to the message to reduce the conflict (Festinger, 1957; Heider, 1946). Messages containing incorrect ideas may trigger helping behaviour from other e-authors (Latané & Darley, 1970), provide feedback and/or correct mistakes. Thus, we derived the second set of hypotheses.

H-2a. Messages expressing correct ideas will increase the likelihood of receiving responses.

H-2b. Messages expressing incorrect ideas will increase the likelihood of receiving responses.

H-2c. Messages expressing justifications will increase the likelihood of receiving responses.

2.3. Invitational form

The third dimension is invitational form; namely, whether the message contains explicit invitations for further discussion. During online discussions, messages can be classified into (1) questions, (2) commands or (3) other statements without invitation (Chiu, 2000; Chen et al., 2012b). According to Joyce and Kraut (2006), messages in a question format are more likely to receive responses in a newsgroup setting. Through the lens of the helping behaviour model by Latané and Darley (1970), questions may increase the likelihood that other e-authors will notice an appeal for help. Therefore, it is reasonable to expect that an e-author who explicitly asks for help is more likely to receive a response in an online academic discussion (H-3a). Davidson-Shivers, Muilenburg, and Tanner (2001) regard commands in online discussions as part of a broader category of soliciting. In a class of 14 graduate students, they found that the students generally provided substantive responses to these kinds of messages. If e-authors perceive the messages in a command format as a solicitation, such messages are likely to receive responses (H-3b). Thus, we formulated the third set of hypotheses.

H-3a. Messages in a question format will increase the likelihood of receiving responses.

H-3b. Messages in a command format will increase the likelihood of receiving responses.

2.4. Emotional expression

The fourth dimension—emotional expression—concerns the affective experience induced in the messages of an online discussion. The expression of an affective experience can be positive, negative or neutral. Jin et al. (2015) showed that in an online social Question & Answer community, e-authors who received positive feedback contributed more knowledge to the community. In this case, positive feedback might have evoked the receivers' positive feelings, and the receivers, in turn, tended to exert more effort in responding. From the perspective of behaviourism (Skinner, 1974), the positive affective experience might serve as a positive reinforcement for increasing post-replying behaviour (H-4a). As for messages expressing a negative affective experience, Lewallen et al. (2014) drew on the research of altruism (see Yalom, 2005, for a review) to explain post-replying behaviour. The result of their study supports the belief that a negative emotional expression is associated with a higher likelihood of others responding. What is more, Ma and Chan (2014) found that altruism had a direct and significant effect on online knowledge sharing on a social media platform. Therefore, anticipating that the messages expressing a negative affective experience are more likely to receive responses (H-4b), we propose the fourth set of hypotheses.

H-4a. Messages expressing positive affective experience will increase the likelihood of receiving responses.

H-4b. Messages expressing negative affective experience will increase the likelihood of receiving responses.

Table 1
A summary of variables and corresponding descriptions.

Category	Variable name	Description (values)
Outcome variable	Responsiveness	Whether a message received a response from others in the discussion (1 = received a response, 0 = received no response)
Explanatory variables		
• Evaluation	Agreement	Agree with a previous message (1 = true, 0 = false)
	Disagreement	Disagree with at least one point in a previous message (1 = true, 0 = false)
• Knowledge content	Correct idea	An idea that is both correct (consistent with both mathematics and problem constraints) and new relative to the discussion (1 = true, 0 = false)
	Incorrect idea	A new idea that is inconsistent with at least one mathematics or problem constraint (1 = true, 0 = false)
	Justification	An action that supports a new idea by linking it to data using a warrant or backing (1 = true, 0 = false)
• Invitational form	Question	Reply as a form of a question (1 = true, 0 = false)
	Command	Reply as a form of a command (1 = true, 0 = false)
• Emotional expression	Positive	Words, symbol or emoticon expressing positive affective state (1 = true, 0 = false)
	Negative	Words, symbol or emoticon expressing negative affective state (1 = true, 0 = false)
Control variables		
	Number of past posts	The number of past posts (integer) by an e-author
	Topic initiator	An e-author who initiates the current topic (1 = true, 0 = false)
	Message length	Total number of words in a message (integer)
	Message number	The position of the current reply message in a topic (percentage of the current message's number divided by the total reply messages)
	Time interval	A log transformation of the time interval (minute) between a reply message's posting-time and its predecessor's posting-time along the same thread

2.5. Other characteristics

Referring to existing studies of online discussions (e.g., Chen et al., 2012b, Chen et al., 2012a; Fang, Chen, Wang, & George, 2018; Tausczik & Pennebaker, 2012), we considered five other characteristics that may affect a message's likelihood of receiving a response: (1) the e-author's number of past posts, (2) topic initiator, (3) message length, (4) message number, and (5) time interval between the message's posting-time and the reply's posting-time (see also Table 1 for the descriptions). For example, the influence of message length was examined in a study by Fang et al. (2018), who found that there was a positive relationship between message length and the number of replying posts in an online community of travellers.

3. Method

3.1. Online discussion forum and data

In this study, we collected and analysed data from an online discussion forum for high school mathematics, which is hosted by Art of Problem Solving (AoPS) Online in the US. As one of the largest mathematics communities on the Internet, AoPS Online aims to help students expand and deepen their mathematical thinking (artofproblemsolving.com). The high school mathematics forum is a non-formal learning environment (Schwier & Seaton, 2013) which is moderated but not facilitated by the AoPS team. More specifically, the forum is not confined to a specific classroom and is publicly accessible and free of charge. It is open to any registered members, who voluntarily read and write posts in the discussion. Participants do not necessarily know one another outside the forum.

We randomly selected 140 mathematics topics distributed in 2016, excluding those topics that received less than four reply messages. Short discussions often have simple structures (e.g., question → answer → acknowledgement), which are fundamentally different from longer discussions that include back-and-forth engagement. Because this study aimed to examine discussions rather than question-answer adjacency pairs, we sampled only topics that included at least four replies.

The topics belonged to the three domains of high school mathematics, namely algebra ($n = 73$), geometry ($n = 29$), and number theory/counting ($n = 38$). At the end of the data collection period (early 2017), the 140 topics had received 1,559 reply messages by 383 e-authors. As a side note, because the provision of personal information is optional in the forum, further analyses of the e-authors (e.g., age, race, and gender) were not feasible. Fig. 1 shows an example of a discussion on an algebra problem called Quadratic 2, including the first few replies.

Taking the Quadratic 2 problem as an example, Fig. 2 shows the tree relationships between the topic (i.e., the first message that initiates a topic) and the replies (i.e., the 12 reply messages). The number '0' denotes the initial problem topic. The numbers '1' through '12' indicate 12 chronological reply messages, where '1' refers to the earliest reply and '12' refers to the last reply. The topic and its reply messages are represented as nodes and linked to each other by multiple threads. Each reply is connected to its previous message (mother node). The topic message and 12 reply messages occur along six discussion threads: (a) 0 → 1, (b) 0 → 2, (c) 0 → 3, (d) 0 → 4 → 5 → 6 → 7, (e) 0 → 8 → 9 → 10 → 12 and (f) 0 → 8 → 9 → 11. The messages in each thread are ordered by time and thus are not necessarily consecutive. In thread (e), for example, message #12 follows message #10 instead of #11. In other words, the post that message #12 is replying to is message #10.

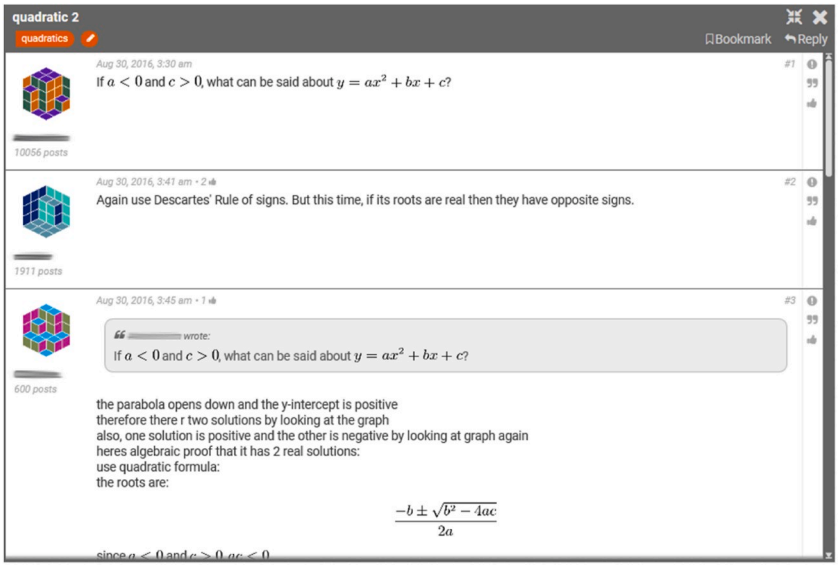

Fig. 1. Screenshot of an online discussion and the first few reply messages. Retrieved from artofproblemsolving.com. Screenshot by author.

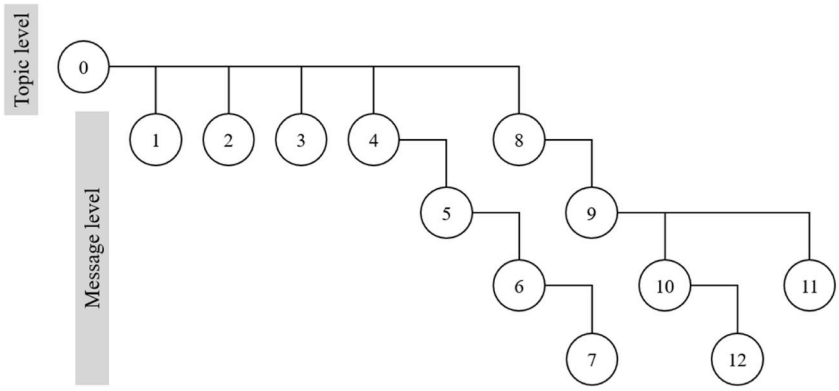

Fig. 2. Tree relationships between the Quadratic 2 problem and its reply messages.

3.2. Variables

Table 1 summarises the variables involved in this study. This set of variables was adopted and modified from Chen et al., 2012a, Chen et al., 2012b. There were three types of variables: outcome variable (*responsiveness*; that is, whether a message received a response from others in the discussion), explanatory variables, and control variables (other characteristics). All the outcome and explanatory variables were binary-valued variables with '1' and '0' representing true and false, respectively. Taking 'non-academic content' in the dimension of knowledge content as an example, '1' signifies that the reply message possessed no academic content nor any problem-related information, such as simple evaluations (e.g., 'No'), simple questions (e.g., 'What?'), or off-topic information (e.g., 'Where are you from?'), whereas '0' represents otherwise.

As shown in Table 1, we created a set of binary variables to represent the evaluation, knowledge content, invitational form, and emotional expression dimensions. Each of these consists of k mutually exclusive and exhaustive categories, which can be fully represented by $k–1$ binary variables in the analysis (Menard, 2002). For example, the invitational form dimension's three categories (question, command, or statement) can be represented by two binary variables. The effects of all three are captured in comparison to one another, using statement as the baseline against the two variables for question and command.

In addition to the current-message variables, the present study also examined the variables describing earlier messages in the same thread because past studies show that recent messages may create a local context that affects the ongoing discussion (Chiu, Molenaar, Chen, Wise, & Fujita, 2014). Constrained by the design of the forum interface, one participant usually responded to the topic or to only one earlier message each time, which helped to identify the relationships among the reply messages.

3.3. Coding

We used a multi-dimensional coding scheme to reduce the number of needed variables, increase inter-coder reliability, and thereby capture the data's complexity. For example, the coding scheme has four dimensions: evaluation (agree, disagree, neutral), knowledge content (null academic content, repetition, new idea), invitation to participate (question, command, statement), and emotional expression (positive, negative, neutral). Because each dimension has three categories, this scheme can capture 81 different types of messages ($81 = 3 \times 3 \times 3 \times 3$). By coding one dimension at a time, a coder chooses among three possible codes only (instead of 81). Thus, the multi-dimensional coding strategy reduces training time and overall coding time, and likely increases inter-coder reliability.

Two student helpers coded the data independently and all disagreements were settled through consensus. Krippendorff's α (2004) for each binary variable was above 0.80, indicating high inter-rater reliability. A coding example (Table A.1) is shown in Appendix A.

3.4. Data analysis

The temporal analysis of the discussion process faced statistical challenges. To address these, the present study adopted statistical discourse analysis (SDA; Chen et al., 2012a, Chen et al., 2012b; Chiu, 2008).

SDA addresses the outcome issues (i.e., nested data, serial correlation, discrete variables) with a multilevel analysis, an I^2 index of Q-statistics, and the logit/probit model. SDA models nested data (i.e., messages within topics) with multilevel analysis. An I^2 index of Q-statistics tested all groups simultaneously for serial correlation of residuals in adjacent events. If the I^2 index shows significant serial correlation, adding the outcome variable value of the previous message often eliminates the serial correlation. Finally, SDA uses a logit/probit model for binary dependent variables (i.e., responsiveness in the present study).

SDA addresses the explanatory variable issues (i.e., sequential nature of data, possible indirect effects, and false-positive effects). A vector auto-regression combines characteristics of sequences of recent messages into a local context to model how they may affect a current message. To consider the indirect effects of explanatory variables, SDA uses multilevel mediation tests. Finally, SDA uses the two-stage linear step-up procedure to reduce false-positive effects (i.e., type I error rate), which is more effective than other relevant methods in computer simulations (Benjamini, Krieger, & Yekutieli, 2006).

Applying SDA to the present data, a logit model was built for the binary outcome variable responsiveness. First, at the topic level ($N = 140$ topics), we entered two binary variables (i.e., algebra, geometry) to represent the three domains of high school mathematics: algebra topics, geometry topics, and number theory/counting topics. A traditional likelihood ratio test is not reliable for the logit model, so we used a Wald test to check for the significance of the explanatory variables (Goldstein, 1995). Non-significant variables were removed in subsequent steps.

At the message level ($N = 1{,}559$ replies), we added the control variables. The variables that describe the message's surrounding properties were added first, which were *message number*, *message length,* and *time interval* between consecutive messages along a thread. Then, the variables that describe the e-author's characteristics were added, which were the e-author's *number of past posts* and whether an e-author was the topic *initiator*. Likewise, non-significant variables were removed in subsequent steps.

We then entered the predictors in order of their temporal occurrence and theoretical importance. First, we tested the evaluation, knowledge content, invitational form and emotional expression hypotheses by entering a list of relevant variables: *agreement*, *disagreement*, *correct idea*, *incorrect idea*, *justification*, *question*, *command*, *positive emotion*, and *negative emotion*. Then, we checked for interaction effects among pairs of significant variables. Non-significant variables and interactions were removed from the specification in subsequent analysis. Next, we checked whether the regression coefficients differed significantly at the topic level. If they did, we kept the additional parameters. Otherwise, we removed them.

Because past studies show that variables belonging to the lagged messages might also affect the outcome variable belonging to a current message (e.g., Chiu et al., 2014), we entered lag variables measuring the properties of earlier messages ($-n$), first at -1, then at -2, and finally -3. An alpha level of 0.05 was used for all statistical tests.

We conducted additional path analysis to estimate the indirect effects of the significant explanatory variables separately. The explanatory variables were entered in temporal order into the path analysis. To increase the readability of the analysis results, we converted the effect (E) of each explanatory variable to an odds ratio, which was indicated by a percentage increase or decrease ($+E\%$ or $-E\%$) in the likelihood of a dependent variable (see Chen et al., 2012b, for the computational details). Finally, to check if the analysis results depended on the Logit distribution, we repeated the above procedure with a probit model.

4. Results

Overall, the analysis results indicate that only the characteristics of a current message significantly predicted its likelihood of receiving a response. In other words, the impact of its previous messages along the same thread (e.g., lag 1 and lag 2) on post-replying behaviour was not significant. Also, a variance components model showed that the outcome variable responsiveness did not differ significantly across topics, so single-level modelling (message level) was adequate. The corresponding probit models produced similar parameter estimates. Furthermore, the final model's Q-statistics and I^2 index showed no significant serial correlation of residuals for the 140 topics. So, the time-series model was likely appropriate.

This section reports the descriptive statistics of the online discussion data. Afterwards, we present the predictability of different variables in each of the five dimensions (i.e. evaluation, knowledge content, invitational form, emotional expression and other characteristics) and the results of hypothesis testing, as summarised in Table 2.

4.1. Descriptive statistics

Table 3 shows the descriptive statistics of the 1,559 reply messages from the 140 topics included in regressions predicting responsiveness. The proportion of messages that received at least one reply was 57.2% ($SD = 0.495$). Among these, 40% of the messages provided an evaluation in which disagreements ($M = 0.219$, $SD = 0.414$) numbered slightly more than agreements ($M = 0.177$, $SD = 0.382$). For the knowledge content dimension, messages expressing correct ideas ($M = 0.359$, $SD = 0.480$) amounted to almost twice those expressing incorrect ideas ($M = 0.167$, $SD = 0.373$). Messages stating justifications constituted 36.6% ($SD = 0.482$). Messages that explicitly invited further response accounted for 24.1%, where e-authors generally used questions ($M = 0.225$, $SD = 0.417$) instead of commands ($M = 0.016$, $SD = 0.126$). In the dimension of emotional expression, only 18.4% of messages expressed affective experience, of which the number of positive experiences ($M = 0.112$, $SD = 0.316$) was slightly higher than the number of negative experiences ($M = 0.072$, $SD = 0.262$). See Table A.2 in Appendix A for the correlation-covariance matrices.

Table 2
Summary of results for hypothesis testing.

Aspect	Hypothesis	Result
Evaluation	H-1a. Messages expressing disagreement will increase the likelihood of receiving responses.	Supported
	H-1b. Messages expressing agreement will decrease the likelihood of receiving responses.	Not supported
Knowledge content	H-2a. Messages expressing correct ideas will increase the likelihood of receiving responses.	Supported
	H-2b. Messages expressing incorrect ideas will increase the likelihood of receiving responses.	Supported
	H-2c. Messages expressing justifications will increase the likelihood of receiving responses.	Not supported
Invitational form	H-3a. Messages in a question format will increase the likelihood of receiving responses.	Supported
	H-3b. Messages in a command format will increase the likelihood of receiving responses.	Not supported
Emotional expression	H-4a. Messages expressing positive affective experience will increase the likelihood of receiving responses.	Not supported
	H-4b. Messages expressing negative affective experience will increase the likelihood of receiving responses.	Not supported

Table 3
Descriptive statistics of the variables ($N = 1{,}559$).

Variables	M	SD	Min	Max
Responsiveness	.572	.495	0	1
Evaluation				
• Agreement	.177	.382	0	1
• Disagreement	.219	.414	0	1
Knowledge content				
• Correct idea	.359	.480	0	1
• Incorrect idea	.167	.373	0	1
• Justification	.366	.482	0	1
Invitational form				
• Question	.225	.417	0	1
• Command	.016	.126	0	1
Emotional expression				
• Positive	.112	.316	0	1
• Negative	.072	.262	0	1
Control variables (other characteristics)				
• E-author's number of past posts	1,073	2,389	1	21,276
• Topic initiator	.210	.407	0	1
• Message length (words)	28.716	40.610	1	463
• Message number (% position in all replies in a topic)	0.545	.288	.029	1
• Time interval (log-transformed minutes)	1.561	1.071	0	6.02

4.2. Predictability of variables

Table 4 shows the significant effects of each explanatory variable on responsiveness. See Table A.3 in Appendix A for the regression results.

4.2.1. Evaluation

When a message expressed disagreement with previous messages, the likelihood of a response would significantly increase from 59% to 67% (+8%; when a disagreement occurred, the message's likelihood of a response was 67%; when a disagreement did not occur, the likelihood was 59%; see Table 4). This supports hypothesis H-1a. See Figure B.1 in Appendix B for an example. The likelihood of receiving a response did not change significantly when a message agreed with previous messages. Therefore, hypothesis H-1b was not supported.

4.2.2. Knowledge content

Messages expressing correct or incorrect ideas were likely to receive a response. For correct ideas, the likelihood of receiving a response would significantly increase from 53% to 62% (+9%), which supports hypothesis H-2a. See Figure B.2 in Appendix B for an example. For incorrect ideas, the increase was even greater and the likelihood of receiving a response would significantly increase from 53% to 76% (+23%). This supports hypothesis H-2b. See Figure B.3 in Appendix B for an example. The likelihood of a response did not change significantly when a message included a justification/explanation. Therefore, hypothesis H-2c was not supported.

4.2.3. Invitational form

When a message explicitly invited further response in a question format, its likelihood of getting a response would significantly increase from 53% to 77% (+24%). This supports hypothesis H-3a. See Figure B4 in Appendix B for an example. For the messages in a command format, no significant effects on responsiveness were found. Therefore, hypothesis H-3b was not supported. Very few

Table 4
Effects of each explanatory variable on responsiveness (R).

Aspect	Explanatory variable (E)	P(R|E) (%)[a]	P(R|~E) (%)[b]	Effect (%)	Standardised parameter coefficients
Evaluation	Disagreement	67	59	+8	+.355**
Knowledge content	Correct idea	62	53	+9	+.381**
	Incorrect idea	76	53	+23	+1.032***
Invitational form	Question	77	53	+24	+1.073***
Other characteristics	Message number	45[c]	76[d]	−31	−1.396***
	Time interval	64[c]	70[d]	−6	−.282***

***$p < .001$; **$p < .01$.
[a] Probability that a message receives a reply if the explanatory variable occurs.
[b] Probability that a message receives a reply if the explanatory variable does *not* occur.
[c] Probability that a message receives a reply when the explanatory variable takes the value of 50% above the mean.
[d] Probability that a message receives a reply when the explanatory variable takes the value of the mean.

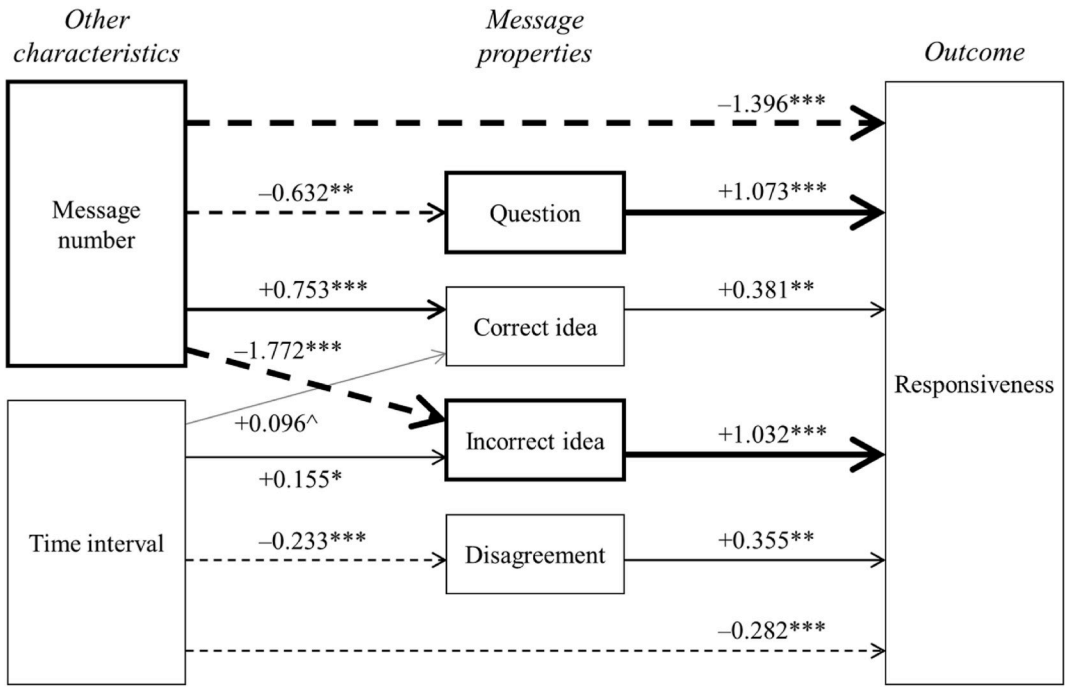

Fig. 3. Path analysis of significant explanatory variables predicting responsiveness. The corresponding value of each arrow is standardised parameter coefficient. To simplify the view, two non-significant paths (message number → disagreement; time interval → question) are omitted. The solid and dashed arrows indicate positive and negative effects, respectively. A thicker line indicates a larger effect size. ***$p < .001$; **$p < .01$; *$p < .05$; ^$p < .1$.

messages included a command in the data set (1.6%). The low occurrence might have limited the generalisability of this result.

4.2.4. Emotional expression

There were no significant effects on the likelihood of a response for messages expressing an affective state. Neither the positive nor negative messages significantly altered responsiveness to messages. Therefore, hypotheses H-4a and H-4b were not supported. It is worth noting that there were relatively few messages expressing emotions (positive = 11.2%; negative = 7.2%). In other words, the affective state was not frequently expressed in the researched online discussion forum. The low occurrence thus might have limited the generalisability of this result.

4.2.5. Other significant characteristics

Results of the analysis show that message number and time interval are two additional characteristics with a significant impact on responsiveness to messages. Specifically, the likelihood of a later message receiving a reply decreased from 76% to 45% (−31%; when a message's number exceeded the mean message number by 50%). Similarly, the likelihood of receiving a response decreased from 70% to 64% (−6%) if the time interval between two consecutive messages was 50% longer than the average wait time.

Table 5 shows the indirect effects of message number and time interval on responsiveness through other variables. First, as message number increased (i.e. the later messages), the likelihood of getting a message that (1) expressed a correct idea increased (+17%), (2) expressed an incorrect idea decreased (−25%), and (3) contained questions decreased (−11%). Second, as the time interval (i.e., the

Table 5
Effects of message number and time interval on other variables.

Explanatory variable (E)	Target (T)	P(T|E) (%)[a]	P(T|~E) (%)[b]	Effect (%)	Standardised parameter coefficients
Message number	Correct idea	44	27	+17	+.753***
	Incorrect idea	8	33	−25	−1.772***
	Question	18	29	−11	–.632**
Time interval	Disagreement	24	28	−4	–.233***
	Correct idea	34	32	+2	+.096^
	Incorrect idea	15	13	+2	+.155*

Note. Two non-significant effects are omitted in the table: message number → disagreement; time interval → question.
***$p < .001$; **$p < .01$; *$p < .05$; ^$p < .1$.
[a] Probability that the target occurs when the explanatory variable takes the value of 50% above the mean.
[b] Probability that the target occurs when the explanatory variable takes the value of the mean.

wait time between two consecutive messages) increased, the likelihood of getting a message that (1) expressed disagreement decreased (−4%) and (2) expressed an incorrect idea increased (+2%). Hence, correct and incorrect ideas, questions and disagreements likely mediated the effects from message number and time interval to responsiveness (see also Fig. 3).

Fig. 3 summarises the path analysis of all significant explanatory variables of responsiveness. As the standardised parameter coefficients suggest, after controlling for message number and time interval, question ($\beta = 1.073, p < .001$) and incorrect idea ($\beta = 1.032$, $p < .001$) had the largest effect on responsiveness, followed by correct idea ($\beta = 0.381, p < .01$) and disagreement ($\beta = 0.355, p < .01$). Together, the variables explained 17% of the variance in responsiveness (Nagelkerke pseudo $R^2 = 0.171$).

5. Discussion

In this study, we adopted statistical discourse analysis to examine how a message's content-related characteristics might affect the likelihood of receiving a response during online academic discussions. We conducted the study in a non-formal learning environment—an open online high-school-mathematics forum that is not confined to a class or a school. The analysis results support the hypotheses about disagreement (H-1a), correct ideas (H-2a), incorrect ideas (H-2b), and questions (H-3a). Apart from content-related characteristics, the results also indicate that message number and time interval affected the likelihood of receiving a response during the discussion. These results are first discussed. The limitations of this study are then acknowledged with recommendations for future research.

First, online messages expressing disagreement were likely to elicit responses. This result confirms research by Tausczik and Pennebaker (2012), whose study of a non-formal online mathematics community found that disagreement significantly encouraged participation but that the effect of the agreement was not significant. In an online discussion, expressing disagreement with an idea makes visible the cognitive conflict between e-authors. As Heider (1946) says of cognitive conflict, 'If no balanced state exists, then forces towards this state will arise' (p. 108). In other words, cognitive conflict creates an incentive for e-authors to contribute and resolve the problem; and resolving the conflict can be meaningful for students, leading to a deeper or broader understanding (Limón, 2001).

Second, both correct and incorrect ideas were likely to elicit responses during the discussion. These results can be explained using the theoretical work on helping behaviour (Latané & Darley, 1970; Yalom, 2005) and cognitive conflict (Festinger, 1957; Heider, 1946). The messages expressing correct ideas might elicit the support or confirmation of other e-authors, whereas those expressing incorrect ideas might trigger corrections. Both actions can be regarded as helping behaviours for problem-solving. Given that there are a large number of members in this study's online discussion, it is reasonable to suppose that not all of them would have the same approach to problem-solving. Therefore, any messages expressing new ideas (correct or incorrect) might create cognitive conflict between e-authors. As a result, the likelihood of receiving a reply increased. In particular, incorrect ideas were more controversial and led to responses and further discussions, consistent with Rooderkerk and Pauwels's (2016) study of a LinkedIn discussion forum showing that controversial posts were more likely to receive comments from others.

Third, messages in a question format were likely to elicit responses. This result was consistent with the study of Joyce and Kraut (2006) in a newsgroup setting. Although altruistic behaviour can lead to post-replying behaviour (Ma & Chan, 2014), e-authors might overlook the need for help and take no action. However, messages in a question format might increase the chance of noticing the need for help (Latané & Darley, 1970) and thus elicit responses. Therefore, questioning is a desirable invitational form for students to ask for further feedback. Our results confirm the value of question prompts in online discussions (e.g., Aloni & Harrington, 2018; Howell, LaCour, & McGlawn, 2017), which can promote online participation.

Finally, message number and time interval also affected the likelihood of messages receiving responses. The results indicate that later messages and delayed reply messages were less likely to receive responses. After multiple e-authors contributed their ideas in an online discussion, they were more likely to resolve the problem and/or cognitive conflict among e-authors. Hence, in the later stage of a discussion, e-authors were more likely to find solutions by reading through the posts in the discussion (Wise, Speer, Marbouti, & Hsiao, 2013), which reduces the incentive to further reply to posts. Delayed replies indicated longer wait times in responding to an earlier message, which might increase the e-authors' feeling of social distance within the online learning environment (Aragon, 2003; Sung & Mayer, 2012) and reduce their likelihood of participating further. Also, as more time goes by, e-authors are more likely to resolve the problem via other means (e.g., asking their teacher) and hence no longer need to visit the forum.

Although we found that the above characteristics of messages can affect the likelihood of receiving responses in online forum discussions, this study has some limitations. First, this study was conducted in a non-formal online learning environment—an open public forum not confined to the classroom. Students might behave differently during discussions in other online learning environments; for example, in a formal course-related forum, students from the same class might know one another well and hence behave differently. Second, this study only examined online discussion of high school-level mathematics problems. The dynamic of an online discussion might differ in other subject disciplines (e.g., social science), in which diverse opinions are common. Third, although the data analysis involved 1,559 reply messages, some categories had few messages. For example, the non-significant results of emotional expression and the interaction of multiple characteristics (e.g., agreement + a question format) were based on a limited number of messages. The generalisability of the results in these aspects was thus limited. Future research can address these limitations by examining student discussions in formal online learning environments, on topics in other subject disciplines, and using a larger dataset to obtain a more comprehensive understanding of students' post-replying behaviour during online academic discussions.

6. Conclusion and implications

This study aimed to identify the content-related characteristics that affect a message's likelihood of receiving a response in online academic discussions on mathematics topics. The results suggest that how a message looks backward (i.e., disagrees with a previous message), posts knowledge content (i.e., adds a new idea, either correct or incorrect), and looks forward (i.e., asks a question) can affect the likelihood of receiving a response. Slow response messages or those posted in the later stages of an online discussion are less likely to receive responses.

These findings about students' natural post-replying behaviours in a non-formal online discussion forum can inform educators as they help students better engage in formal online discussion settings. First, educators can encourage students to critically evaluate previous messages during a topic discussion. As expressing disagreement elicited further responses among these students, educators can consider whether facilitating such an idea-exchanging process might enhance students' understanding of the subject content. Second, educators can encourage students to express new ideas in online discussions. Whether the ideas are correct or incorrect, other students might engage with them, to confirm or correct them. Thus, students might benefit from such exchanges. Third, these messages with questions increased peer engagement and sustained online discussions. Future studies can test whether incorporating or adding question prompts to online discussions facilitates discussion processes. Finally, future studies can determine whether encouraging students to provide timely responses early in the online discussion increases feedback from other students. In this way, such students might be more involved in the discussion.

CRediT authorship contribution statement

Gaowei Chen: Conceptualization, Methodology, Formal analysis, Writing - original draft. **Chung Kwan Lo:** Investigation, Validation, Writing - review & editing. **Liru Hu:** Data curation, Writing - review & editing.

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Appendix A. Tables

See Tables A.1 to A.3.

Table A.1
Coding of the first 7 reply messages of a topic "Cool math problem made by me!" in the discussion forum

No	E-author ID	Message content	R	Evaluation		Knowledge content			Invitational form		Emotional expression	
				Ag	Dg	CI	InI	Jus	Qu	Cm	Pos	Neg
0	e-author 0	Find the smallest positive integer X such that X, X+2, X+3, X+4, X+6, are all the products of two primes.										
1	e-author 1	Do the two primes have to be distinct?	1	0	0	0	0	0	1	0	0	0
2	e-author 2	I would assume otherwise. (Of course I have no authority over this)	0	0	0	1	0	0	0	0	0	0
3	e-author 0	[E-author 1], no they are not necessarily distinct	1	0	1	1	0	1	0	0	0	0
4	e-author 3	I would guess 1 but 1 is not prime	0	0	0	1	0	0	0	0	0	0
5	e-author 3	[Cite message #0] does this mean two distinct primes???	1	0	0	0	0	0	1	0	0	0
6	e-author 2	[Cite message #3 to reply to #5]	1	0	0	0	0	0	0	0	0	0
7	e-author 3	thanks …	0	1	0	0	0	0	0	0	1	0

No = Message number; R = Responsiveness; Ag = Agreement; Dg = Disagreement; CI = Correct idea; InI = Incorrect idea; Jus = Justification; Qu = Question; Cm = Command; Pos = Positive; Neg = Negative.

Table A.2
Correlation-variance-covariance matrices of responsiveness and their significant predictors

	Variable	1.	2.	3.	4.	5.	6.	7.
1.	Responsiveness	.245	–.035	–.094	.035	–.013	.030	.018
2.	Message number	–.245	.083	.076	–.009	.016	–.018	.000

(*continued on next page*)

Table A.2 (*continued*)

	Variable	1.	2.	3.	4.	5.	6.	7.
3.	Time interval	–.178	.248	1.147	–.008	.039	.006	–.041
4.	Question	.171	–.075	–.017	.174	–.058	–.002	–.013
5.	Correct idea	–.053	.115	.075	–.290	.230	–.060	.020
6.	Incorrect idea	.163	–.170	.016	–.015	–.335	.139	.018
7.	Disagreement	.088	.001	–.092	–.076	.103	.116	.171

Note. The lower left triangle contains the correlations, the bold numbers along the diagonal are the variances, and the upper right triangle contains the covariances.

Table A.3
Significant, standardised parameter coefficients of hierarchical set logistic regressions predicting responsiveness (with standard errors in parentheses)

Predictor	3 logistic regressions predicting responsiveness		
	Model 1	Model 2	Model 3
Message number	−1.582*** (0.193)	−1.551*** (0.196)	−1.396*** (0.201)
Time interval	−0.248*** (0.051)	−0.240*** (0.052)	−0.282*** (0.054)
Question		0.894*** (0.139)	1.073*** (0.149)
Disagreement		0.487*** (0.134)	0.355** (0.138)
Correct idea			0.381** (0.128)
Incorrect idea			1.032*** (0.175)
−2 * Log Likelihood	2009.729	1955.337	1917.327
Nagelkerke pseudo R^2	0.099	0.142	0.171

Note. Significant constant term is omitted.
*$p < .05$, **$p < .01$, ***$p < .001$.

Appendix B. Figures

See Figures B.1 to B.4. Retrieved from artofproblemsolving.com. Screenshot by author.

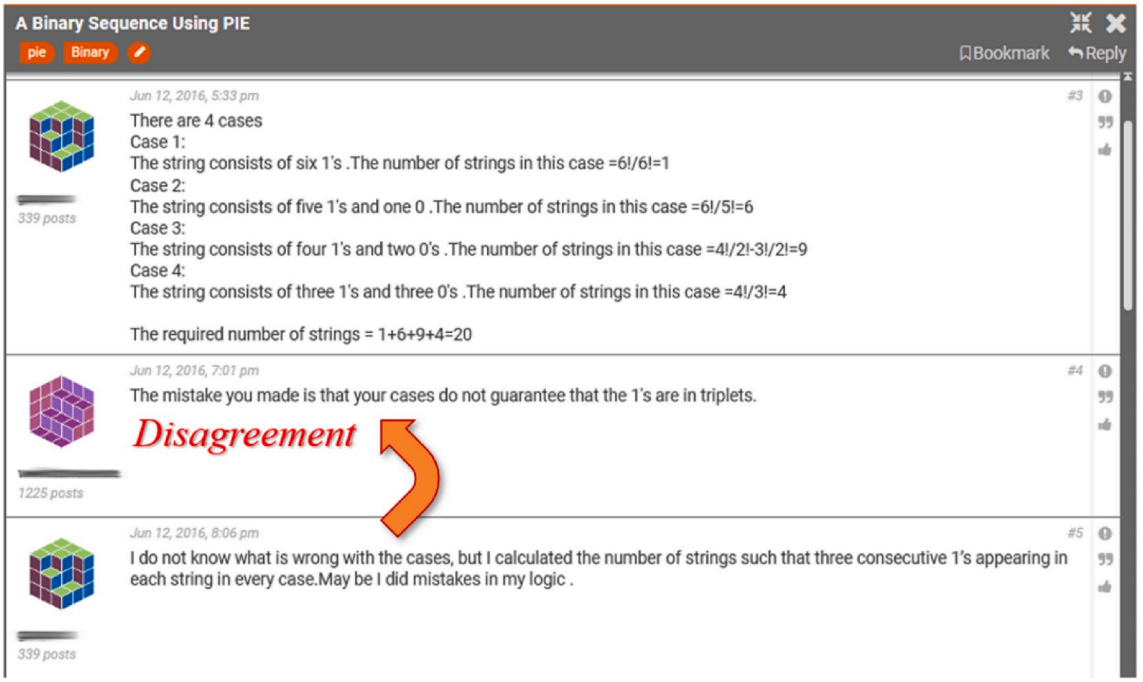

Fig. B.1. An example of responding to a disagreement.

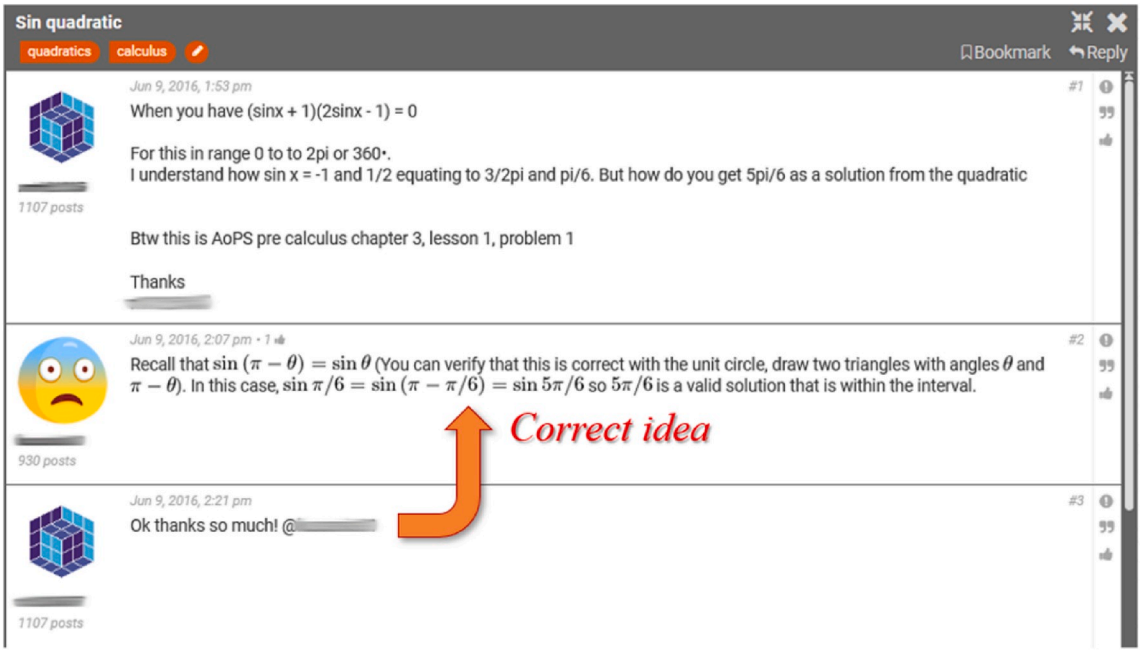

Fig. B.2. An example of responding to a correct idea.

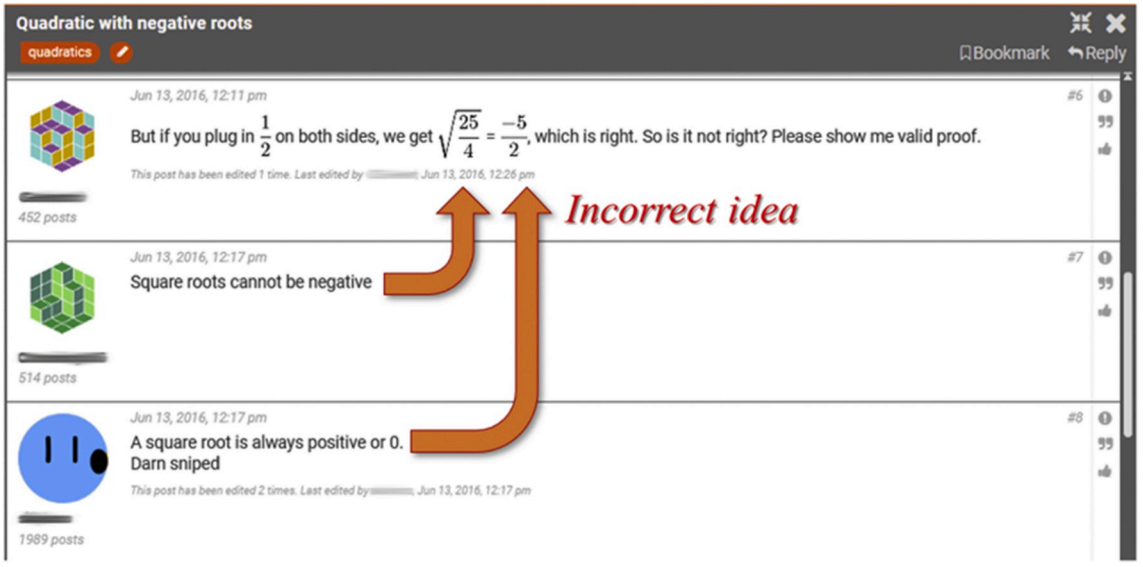

Fig. B.3. An example of responding to an incorrect idea.

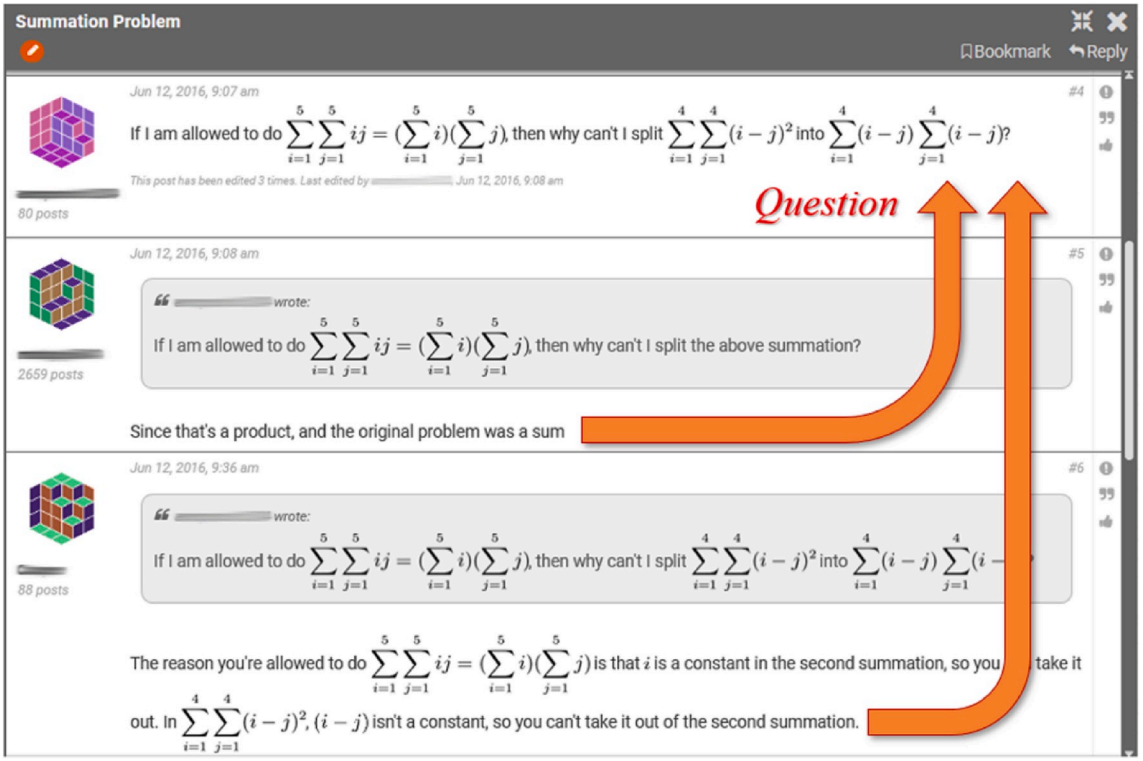

Fig. B.4. An example of responding to a question.

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