The influence of task activity and the learner's personal characteristics on self-confidence during an online explanation activity with a conversational agent

Yugo Hayashi
Ritsumeikan University
2-150 Iwakura-cho,Ibaraki
Osaka,567-8570,Japan
y-hayashi@acm.org

Yugo Takeuchi
Shizuoka University
836,Ohya,Suruga-ku,Shizuoka
Shizuoka,422-8529,Japan
takeuchi@inf.shizuoka.ac.jp

ABSTRACT
This study investigated the factors underlying the estimation of learner self-confidence during explanations with a conversational agent in an online explanation task. Based on reviews of previous studies, we focused on how factors such as the learner's task activities and personal characteristics can be predictors. To examine these points, we used an online explanation task, which was run by a conversational agent for students in a classroom on information processing psychology (n=99). We asked the participants to make text-based explanations to the agent in a question-and-answer (Q&A) style, and clarified a particular concept that was taught in a previous lecture in the class. The results show that an increase in the amount of actual task work for explanations and personal characteristics (such as social skills) helped to predict higher self-confidence. The findings have implications not only for knowledge of how such factors might influence learner self-confidence in an online explanation task, but also for the design of online tutoring systems that can automatically detect learner confidence using these variables, and facilitate learning adequately based on such data.

1. INTRODUCTION
Networked learning such as the use of massive open online courses (MOOCS) and tutoring systems, which include social networking services (SNS) has seen many advances in recent years and has become a popular way of supporting learning through social interaction. Such environments allow learners to interact with each other through conversation, and have drawn the attention of many socio-constructionists in the field of learning science. Numerous investigations in this field focus on discussion boards [5, 25], and an emerging number of studies have examined the technological side of research. Moreover, these studies have explored how to detect the learner's conversational behavior. Researchers in artificial intelligence education (AIED) have been investigating the use of conversational agents (CAs) in online environments [20] and have explored the use of agents that play the role of peer learner, whereby they interact socially as discussants in a serious game-based environment [20]. Some research on online tutoring systems examines the use of agents that play the role of the student, whereby learners absorb information through teaching the agents [16, 17]. One of the most important points of learning by teaching is that the learner can reflect on his ideas by observing his externalized thoughts. In the context of social learning, metacognitive abilities might help him identify the perspectives of other learners/agents to establish shared knowledge and successfully coordinate with one another.

Despite concerns surrounding the effects of social learning on social coordination skills and metacognitive abilities, not many experimental investigations have explored the learner's task efficiency and metacognitive process, such as confidence during interactions with a CA. Our study centers on the learner's metacognitive capacity; for example, in relation to confidence evaluations in an explanation activity with a CA. We investigated how the learner's task activity and personal characteristics impact his confidence level during tasks, and propose a model to understand learner confidence during online tutoring with an agent. We also discuss how our model could predict learner confidence, and subsequently develop an automated tutoring system that can collaboratively respond based on learner confidence.

1.1 Conversational Agents and their use in online Learning
The number of studies on computer-based learning that employs intelligent tutoring systems has grown rapidly over the past three decades[14, 27]. Advances in language technology have enabled the development and use of CAs, which can act as peers learners or mentors, and have made progress in terms of facilitating learning activities[10, 8]. Initial studies focused on the use of embodied CAs that act as educational companions or tutors and facilitate the learning process as it relates to motivation[4]. Moreover, recent research has examined the implications of such technology on learning gains through learning by doing [1]. Many studies investigate the use of agents capable of handling natural conversation; these agents are developed based on conversational dialog models, and have demonstrated the successful use of tutoring in social interactions. One example is AutoTutor, a system that

allows students to engage in conversations for their projects. Recently, more advanced online tutoring systems, such as Operation ARIES!, have employed CAs [20] where learners absorb information through web-based tasks in which they talk with CAs. Other tutoring systems have begun to incorporate elements such as SNS [13]. In such cases, learners can interact with other learners and CAs; they must use metacognition to monitor their own perspectives as well as those of their peers in order to better coordinate with one another. Many important psychological issues have not yet been explored in depth; for example, how learners develop their confidence by reflecting on activities in such an environment. In the next section, we will look at some of these points based on reviews of related studies.

1.2 Self-confidence and learning

The 2015 report of the Programme for International Student Assessment (PISA) an initiative of the Organisation for Economic Co-operation and Development (OECD) identifies several types of skills such as prior knowledge, personal characteristics, collaborative capacity, and problem-solving skills. These abilities were assessed using pedagogical CAs, which acted as peer learners and tutors. The report mentions self-monitoring as an important skill because learners must be able to keep track of how their abilities, knowledge and perspectives affect their interactions with other agents in relation to the task at hand [23]. Monitoring skills can be detected through evaluations of self-confidence; this issue has been broadly examined in cognitive psychology.

Cognitive psychology research has a long history of studying metacognition, such as self-monitoring of task efficiency, which is deeply linked to performance [19]. According to the literature, problem-solving involves conscious, step-by-step observation of one's problem-solving behavior. Throughout this process, one can estimate the likelihood of the ongoing task having success or failure. In terms of learning activities, high confidence is known to reflect higher quality mental representations of a task, and is associated with long-term recall [7]. In this sense, a hypothesis can be deduced, such as that the actual task activity might facilitate the learner's monitoring; for example, regarding the self-evaluation of one's confidence about a task. Interestingly, some educational psychology studies have revealed that self-assessments of learning achievement are negatively correlated with learning performance [9]. One explanation for this outcome might be that learners have inherent cognitive limits that hinder simultaneous monitoring and execution of a task. They might also have individual differences in terms of their capacity to self-monitor. Additional types of individual skills that can be captured by self-assessments might play a role in self-monitoring. In this context, we investigated participants' ability to self-monitor their confidence about a task activity. Next, we analyzed the relationship between self-monitoring and the personal characteristics, which might also affect confidence level.

1.3 Personal characteristics and Learning

Along with concerns raised in the previous section about personal characteristics, recent reports have shown that qualities such as attitude, interpersonal skills, personal traits, and motivation can influence individual learning activities[23]. Studies examining such personal features have shown that these factors indeed influence learning; for example, when it comes to thinking style [26]. In the context of this study, where learners interact socially with an agent, it is important to focus on the learner's personal qualities as they relate to social interaction and communication skills. Some research has explored the use of Big-Five questionnaires [15], which center on personal characteristics, such as social skills. Previous studies have indicated that learners with poor social skills might have lower collaborative performance [21]. Other studies by [12] have investigated how learners' skills influence their performance during an online, concept-learning tutoring task with a pedagogical Conversational Agent (PCA). During in this task by [12], learners were guided by a PCA that helped them formulate their explanations of a key concept taught in a large-scale class. The results show that learners with higher social skills performed better on explanation activities with the PCA. Taking this into consideration, personal characteristics such as social skills will also influence metacognitive states, which are related to task performance. Thus far, no investigations have delved into the relationship between social skills and self-confidence; however, this study does. Based on this, we focus on a particular situation whereby most studies using agents have not yet fully examined the influence of personal characteristics on learning activities.

1.4 Goal and Hypothesis

This study investigates how the learner's task work influences metacognition of his/her work, and consequently, self-confidence. Furthermore, we examined how personal characteristics, which are considered important for inter-personal interactions, impact both the task activity and the learner's metacognition of the task. To explore these points, we used an online explanation task where we asked learners to give explanations to a social CA in a Q&A style, and to chat about a particular concept that was taught in a previous lecture. Based on reviews of previous research on learning activities and metacognition, we hypothesized that an increase in the amount of actual task work, such as giving many explanations to an agent, would enhance self-confidence about one's work (H1). For our second goal, we focused on the relationships between personal characteristics and work on explanation activities, as well as the learner's metacognition of that work. We posited that higher interpersonal skills would increase the number of actual explanation activities in relation to the social agent (H2-a), and would also enable metacognition of the student's explanations (H2-b). In the next section, we will demonstrate how we analyzed these points.

2. METHOD

2.1 Participants and conditions

Ninety-nine (Mage: 20.52, SD: 1.60) Japanese university students majoring in psychology participated in this study. The students, whom we call learners, were taking a lecture class on information processing psychology in 2014 and used the system as part of their coursework. The learners were taught about 30 basic concepts of human information processing such as top-down processing, neural networks, Bayesian models, and expert systems.

2.2 Procedure

After the participants attended lectures about the basic concepts taught in class, they took part in an online tutoring task that was valid for two weeks. They logged into the web system using their ID and password, and worked on the task based on their personalized page. They could only access the system on campus using the computer terminals located there. Only members of the class were registered in the system and were assigned to groups consisting of 4-5 students. In each group, the participants worked on the same materials, and the system provided them with updated information about their fellow members.

The aim of the task was to facilitate learner's self-explanations[6] of the basic ideas they learned in class by conversing with social agents though online texts. As they began the task, the agent appeared on their screens and asked them questions about a specific concept. The questions consisted of 17 types such as: "Can you explain the key term regarding how it functions?" "How do you use it in your daily life?" and "Can you think of a concept similar to this one?" Learners were able to restart and continue the task, even if they terminated it during the Q&A session. After they answered one question, the page switched to an assessment page, and the system asked them to assess their confidence level. As will be explained in the following section, this was done to measure the degree of self-confidence. Afterward, learners received feedback from the social agent, along with examples from other members when inputs were entered into the database. If there was no updated information from classmates, the system used a database from the previous year instead. As learners finished answering all 17 questions, they completed the task. This activity lasted an average of 30 minutes.

2.3 System

The system was operated on an Apache web server via a CentOS server. The scripts of the web pages were written in PHP, JavaScript, HTML and CSS. MySQL was used for the database. This system is a modified version of [11] and is called "Web-based Explanation Support with Conversational Agent" (WESCA). The system has a database that manages thirty different key terms that were selected from the class material; one was assigned to each of the learners according to their ID numbers. The agent in the system responds to the learner's text sentences and the number of questions based on the bag-of-word method. The system can also retrieve other members' answers (using them as examples) from the logs based on year, and data from previous years if there is no updated information. The system also features social awareness functions such as evaluating the other learners pushing the "like" button. The current version does not have any functions to show learners how many likes they have received during the task.

2.4 Measures

This study focuses on three factors: (1) degree of self-confidence while interacting with the agent, (2) the amount of interaction with the agent, and (3) the effects of personal characteristics on social skills. In the following section, we describe the types of measures that we used to capture these factors.

2.4.1 Meta cognition: Self-confidence

To capture learner self-confidence during the participants' explanations, we collected assessments based on confidence level about the explanations for each Q&A session with the agent. Learners were required to input their self-confidence level based on a seven-point scale (-3: not very confident to 3: very confident). As with the number of interactions, we analyzed the average level of confidence for each individual, and used these levels as representative values for each participant.

2.4.2 Number of interactions: The amount of words used to explain

We calculated the number of interactions based on the number of words that the learners input while responding to the agent. For each individual learner, we used the average number of words that were input into the system as a representative value for the number of interactions with the agent.

2.4.3 Personal characteristics: The autism spectrum quotient (AQ) score

We assessed the degree of social communication skills based on the questionnaire, which was originally developed in [3] and translated into Japanese. This questionnaire appraises social skills based on the autism spectrum quotient (AQ) and was originally was used to investigate whether healthy adults had symptoms of autism. The questionnaire consists of 50 questions covering five different domains associated with the autism spectrum: (1) social skills, (2) attention switching/tolerance for change, (3) attention to detail, (4) communication skills, and (5) imagination. For each question, learners assessed how strongly they felt about themselves on a five-point scale (1: Doesn't match, 5: Does match). For example, a question about social skills would be, "I like to do activities that require interacting with others.'" The higher the score, the lower the learner's degree of autism, which indicates strong social communication skills. For each learner, we calculated the five factor scores of domains (1) to (5) using factor analysis, and used this as the representative value for analysis.

3. RESULTS

To examine our two hypotheses, we first explored how learners' explanations that they gave to the agent influenced their self-efficiency. For this point, we investigated the relationships between (1) the number of explanations given to the agent and the degree of learner self-confidence regarding the achievement of the activity. Then, we looked at how individual characteristics (such as social communication skills) influenced both the number of explanation activities and self-confidence. For this aspect, we analyzed (2) the relationship between the AQ scores and the number of explanations and confidence levels.

3.1 Explanation activities and self-confidence

First, we conducted a correlation analysis using the Pearson correlation coefficient to identify any relationships between the two variables, as well as the average number of words used during the explanation activity, and the average confidence level about the explanation given to the agent. The findings show that there were significant relationships between the two variables (r = 0.211. $p < .05$). Figure 1 describes the correlations between the two variables. Next,

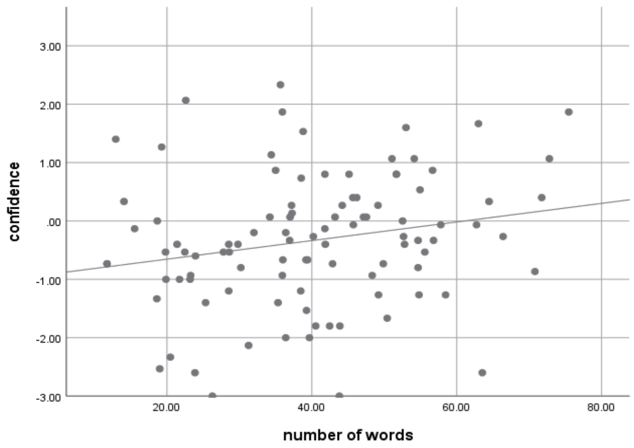

Figure 1: Relationship between learner's confidence and typed words.

Table 1: Results of correlations between personal characteristics and number of words

	# of words
1. social skills	0.051
2. attention switching	-0.023
3. attention to detail	0.149
4. communication skills	0.076
5. creativity	0.034

we explored how explanation activities influenced confidence level by conducting a single regression analysis. We employed the evaluations of confidence as the dependent variable, and number of words used during explanations as the independent variable. We used the forced entry method to perform the analysis and acquired the regression equation with the coefficient of determination (R^2=0.035 by $p < .05$). These results suggest that the actual performance of interactions (such as explanation activities) facilitates metacognition, thus supporting hypothesis H1.

3.2 Personal Characteristics

3.2.1 Personal Characteristics and explanation activities

Next, we analyzed the correlations between the scores of the five domains and the types of words to see how the personal characteristics considered by the AQ questionnaires related to task activity. More specifically, we examined the correlation between the number of words used for the explanations and each of the five AQ domain factors: (1) social skills, (2) attention switching/tolerance for change, (3) attention to detail, (4) communication skills, and (5) imagination. Table 1 depicts the correlations between the variables.

The outcomes of the analysis of the Pearson correlation coefficient revealed no significant links between any of the AQ categories. This indicates that personal qualities captured from the AQ scores do not have any influence on explanation activities with the agent. This shows that hypothesis H2-a was not supported.

Table 2: Results of correlations between individual characteristics and learner's confidence

	leanrer's confidence
1. social skills	0.312
2. attention switching	0.211
3. attention to detail	-0.164
4. communication skills	0.170
5. creativity	-0.025

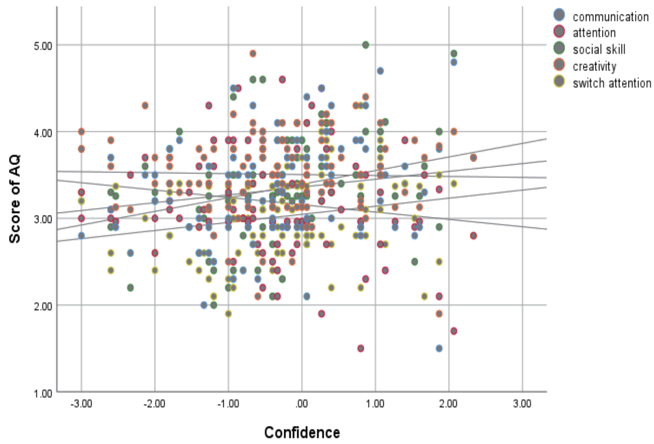

Figure 2: Relationship between each AQ score (Y-axis) and learner's confidence(X-axis).

3.2.2 Personal Characteristics and self-confidence

Next, to see how personal characteristics considered by the AQ scores were related to confidence, we looked at the correlations between the AQ scores and confidence level. For each of the five AQ factor scores, we explored the correlation with confidence level. Table 2 shows the correlations between the variables. The findings of the analysis of the Pearson correlation coefficient revealed significant links between confidence and three variables from AQ: (1) social skills (r = 0.312. $p < .01$), (2) attention switching/tolerance for change (r = 0.211. $p < .05$), and (4) communication skills (r = 0.170. $p < .05$). To see if personal characteristics considered by the AQ scores influenced the number of explanation activities, we conducted a multiple regression analysis. Figure 2 shows the outcomes of the correlations between the two variables. We employed the number of words as the dependent variable and the five AQ factors as the independent variables. We used the forced entry method to perform the analysis, and acquired a regression equation with the coefficient of determination R^2=0.137 by $p < .05$. Table 3 shows the summary of the multiple regression analysis. These findings demon-

Table 3: Summary of the mutiple regression analysis

	regression coefficient B
1. social skills	.368
2. attention switching	.044
3. attention to detail	-.041
4. communication skills	.004
5. creativity	-.203

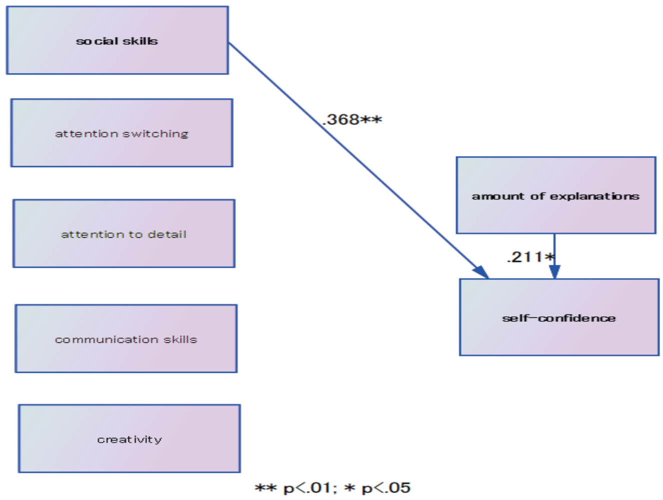

Figure 3: Overall results of AQ score amount of explanations and self-confidence. Indices's indicate the regression coefficient B.

strate that only the variable of social skills influenced learner evaluations of confidence. This indicates that personal characteristics influence learners' metacognition of their learning activities, thus supporting hypothesis H2-b. Figure 3 portrays the summary of the results, including path variables. This figure shows the model of how personal characteristics and actual task work facilitate self-confidence. Our data analysis suggests that this model could potentially predict learner self-confidence, which we will discuss further in the next section.

4. DISCUSSION

4.1 Developing an automatic tutor to detect learner self-confidence

Our results show that self-confidence was related to the task activity, as well as personal traits (such as social skills). Considering these findings, the actual amount of words input and previously self-evaluated personal scores can help predict confidence level. Therefore, we can use this model to develop systems that can become aware of the learner's subjective states. We can also employ it to design pedagogical agents that could prompt learners to request help or encourage those with low confidence. As discussed earlier, learner self-confidence is highly related to task performance[7]; identifying learners' cognitive states might facilitate self-efficiency [2] during the task, which could result in higher learning performance. Discussions about learning performance could go beyond the topic of this paper. I would like to show how the proposed model could be used to automatically predict learner self-confidence during the task. For this investigation, we used machine learning to see how the categorical factors that were extracted from the previous analysis might be optimal for detection. We used linear discriminant analysis (LDA), using confidence as the dependent variable and the number of words and social skills score as independent variables. Confidence was labeled as a binary of high/low based on the median of the acquired data set. The results of the LDA show an accuracy rate of 66.7%, which indicates a relatively high validation of categorization. There have been recent attempts to detect and model self-efficiency in tutoring systems[18]. However, not many studies focus on personal characteristics as predictors. In this sense, our model could provide a new way to capture learners' subjective states. However, as noted above, more integrated investigations should be carried out, along with an analysis of learners' performance during the explanation activities. To do so, we should evaluate learners' output messages and see how they relate to the variables acquired in this study.

4.2 Motivating learners via socialized feedback from the conversational agent

The system used in this study features functions such as providing feedback about other group members' explanations. Moreover, learners were able to assess each other's explanations by clicking on the "like" buttons, as in SNS. These social functions are adequate for motivating learners and reducing the dropout rate. One of the methods used to facilitate learner self-efficiency in such educational environments could be designed by providing feedback, such as how many "likes" they receive during their activities. Telling learners that they have been nominated as good explainers in the group is another way to motivate them. The CA can provide such feedback, as it is well-known that people can praise each other in human-computer interactions [22]. Related studies from our research group have been developing systems through which students can request help online, as well as systems that support teachers in programming classes[24]. Learners in the classroom use the system and report the ongoing progress of their programming tasks. As they complete each task, an agent installed in the system contacts the learner and sends a request for him to help other classmates who are still stuck working on a problem. The system aims to increase learners' self-esteem by approving/selecting him to help his classmates. The study focuses on motivation when a learner becomes a teacher, as well as on learning in the domain of programming skills. In future, the system to be introduced in this current study might utilize such features, the goal being to encourage learners to use these types of help-requesting functions provided by CAs.

5. CONCLUSIONS

This study focused on self-confidence during explanations with a CA in an online explanation task. The study aimed to understand how the actual activity conducted during the task influenced the learner's metacognitive state. Moreover, based on the literature on personality and individual differences, we investigated how interpersonal traits related to social communication could become predictors for the learner's task activity and his metacognition of it. Using an online tutoring system developed by [11], we collected learners' activity logs of explanations, evaluations of their confidence, and AQ scores. The results of the regression analysis revealed that increasing the amount of actual task work, such as giving many explanations to a social CA, enhances learners' self-confidence about their work, thus supporting hypothesis H1. The analysis of personal characteristics showed that social skills influence self-confidence (thus supporting H2-b); however, they do not influence the actual task work (H2-a is thus not supported). These outcomes indicate that personal traits affect self-confidence in interactions with a social CA. These findings have new implications for designing tutoring systems that can assess and detect learner confidence during online learning activities. An additional analysis using machine learning has also been conducted to investigate if the model suggested in this study could be used to automatically detect learner confidence and thus showed the effectiveness.

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