Understanding Cooperative Learning in Context-Aware Recommender Systems: A User-System Interaction Perspective

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Abstract
Context-Aware Recommender Systems (CARSs) are becoming commonplace. Yet, there is a paucity of studies that investigates how such systems could affect usage behavior from a user-system interaction perspective. Building on the Social Interdependence Theory (SIT), we construct a research model that posits cooperative learning as a trait of users’ interactions with CARSs and outline a proposed empirical study for validating the hypothesized relationships in this model. Specifically, we draw on interdependencies in human-machine relationships to postulate positive interdependence as an antecedent of users’ promotive interaction with CARSs, which in turn, dictates the performance of such recommender systems. Furthermore, we introduce scrutability features as design interventions that can be harnessed by developers to mitigate the impact of users’ promotive interaction on the performance of CARSs.

Keywords: Context-aware, recommender systems, cooperative learning, user-system interaction, human-machine relationships
Introduction

Technological advancements in the likes of Radio Frequency Identification (RFID) and Internet of Things (IoT) have enabled contextual information of individuals (e.g., location, time, type of device and weather) to become readily accessible. Gartner’s 2006 Emerging Technologies report indicated that context-aware mobile applications is fast becoming one of the most pervasive technologies in recent years (cf. Zhang et al. 2009). HEXA RESEARCH, a market research and consulting company, predicted that the annual growth of the global context-aware computing market is expected to exceed 30% from 2016 to 2024.

Context-Aware Recommender Systems (CARSs) constitute one of the most prominent applications of context-aware computing. Setten et al. (2004) alleged that the goal of context-aware computing coincides with that of recommender systems because both are aimed at offering relevant services to consumers. Consequently, the infusion of context-aware capabilities into recommender systems could bolster service levels by tailoring recommendations to match users’ circumstances. Likewise, Adomavicius and Tuzhilin (2015) asserted that contextual information is critical to the performance of recommender systems. Indeed, CARSs are prevalent in our daily lives. For instance, Yelp, a context-aware mobile application which publishes crowd-sourced reviews about local businesses, could recommend restaurants based on consumers’ time and location: consumers will receive nearby restaurant recommendations for a late-night bite if they were to open the mobile application at night. Not only can CARSs enhance user experience, they can also deliver economic value. As estimated by Amatriain and Basilico (2015), nearly 75% of the content people watch in Netflix is obtained via recommender systems.

Although CARSs are becoming predominant, their development is still in the infancy stage and usability challenges remain unresolved (Zhang et al. 2009). To-date, the bulk of the research on CARSs is centered on technical issues like system architecture rather than user-centered design. Furthermore, Zhang et al. (2009) noted that most studies on context-aware mobile applications are conceptual in nature and do not take into account user evaluation. This in turn contributes to a limited understanding of context-aware systems from users’ perspective within the information systems community (Zhang et al. 2009). Zhang et al. (2009) hence called for further inquiries into how context-aware applications affect users.

Because extant literature tends to focus on improved recommendations as desirable outcomes of CARSs (Gorgoglione et al. 2011; Panniello et al. 2016), user-system interactions often take a back seat in past studies. There is a paucity of studies investigating CARSs from a user-system interaction perspective. Compared to traditional recommender systems, two characteristics are salient: increased complexity and enhanced interactivity of CARSs (Adomavicius and Tuzhilin 2015). To acquire contextual information of an individual (e.g. location, activities), CARSs need to interact more intensely with users. At the same time, to harness contextual information appropriately, users would be confronted with more foreground or background interactions (e.g., monitoring user activities to analyze behavior patterns) (Ishii and Ullmer 1997). Consequently, the interaction process is vital to usage experience in CARSs. As remarked by Knijnenburg et al. (2012), evaluations of user-system interactions are likely to alter user experience in recommender systems because user-friendly interfaces, preference elicitation methods, and algorithmic structures may contribute to system-, process- and outcome-level user experience respectively. In this sense, CARSs could improve the accuracy of recommendations by incorporating contextual information into the recommendation process (Adomavicius and Tuzhilin 2015).

Building on the Social Interdependence Theory (SIT), we advance a research model that posits cooperative learning as a trait of users’ interactions with CARSs and outline a proposed empirical study for validating this model. Specifically, through this study, we endeavor to provide an answer to the following research question: How do interactions between context-aware recommender systems and users influence the performance of such systems?

Theoretical Foundations and Hypotheses Formulation

Consistent with Burke (2002), we conceive a recommender system as any system that produces individualized recommendations as outputs or directs users in a personalized fashion to relevant products/services in a vast space of plausible options. In the same vein, we subscribe to the work of Dey (2000) in defining context as: “any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between the user and an
application, including the user and application themselves”. Taken together, a widely-accepted conceptualization of context-aware systems is that such systems utilize “context to provide relevant information and/or services to the user, where relevancy depends on the user’s task” (Dey 2000). By extrapolation, a CAR is one that leverages on context to provide targeted recommendations to users.

**Context-Aware Recommender Systems: A Synthesis**

Given an abundance of past studies on CARSs, Adomavicius and Tuzhilin (2015) have classified extant literature on CARSs into four distinctive research streams, namely fundamentals, algorithms, evaluation, and engineering. The ‘fundamentals’ research stream is interested in disentangling basic concepts like what is context or how to model context in recommender systems. Conversely, studies belonging to the ‘algorithms’ research stream concentrate on enhancing existing recommendation algorithms. Finally, the ‘evaluation’ research stream is concerned with the performance assessment of CARSs whereas the ‘engineering’ research stream entails studies that put forth architectural considerations for implementing CARSs. It should be noted that there are also studies belonging to more than one research stream.

As noted by Zhang et al. (2009), the majority of studies on context-aware computing were conducted from a technical perspective and fall under the ‘algorithms’ research stream. For example, Sundermann et al. (2016) proposed an innovative context extraction method in CARSs. By assessing similarities among textual data visited by users, a topic hierarchy, which is oftentimes regarded as contextual information, could be extracted (Sundermann et al. 2016). In the same vein, Adomavicius et al. (2005) elaborated on a multidimensional approach for modeling contextual information in CARSs.

For the ‘engineering’ research stream, contextualized applications that are dedicated to specialized fields have been developed, such as recommender systems dealing in mobile applications (Karatzoglou et al. 2012), movies (Colombo-Mendoza et al. 2015), restaurants (Gallo et al. 2013), and tourism (Setten et al. 2004), just to name a few. Conversely, for the ‘evaluation’ research stream, apart from assessing CARSs in accordance with baseline performance within datasets, there is an increasing number of studies that are focused on system evaluation from users’ perspective. Gorgoglione et al. (2011), through a controlled experiment, concluded that CARSs outperformed randomized and content-based recommender systems with respect to trustworthiness and purchasing behavior. Extending Gorgoglione et al. (2011)’s work, Panniello et al. (2016) revealed that CARSs surpass conventional recommender systems by improving the accuracy and diversification of recommendations, which in turn impacts trustworthiness.

In contrast to the preceding three research streams, there is comparatively less progress being made to the ‘fundamentals’ research stream (Adomavicius and Tuzhilin 2015). Due to the complexity of CARSs, researchers continue to be divided on rudimentary issues related to the definition and characterisation of context. This represents an area of concern because there would be a negative spillover effect on studies in the other three research streams if we are unable to answer fundamental questions relating to unique theoretical characteristics of CARSs. Among these limited studies, questions regarding user-system interactions are crucial for comprehending CARSs given their complexity and enhanced interactivity (Adomavicius and Tuzhilin 2015). Because CARSs deal in greater diversity in data sources (e.g., users, products, location, time, weather and activity), it is much more sophisticated for such systems to generate useful recommendations. At the same time, to acquire multiple sources of information, CARSs require user interventions. CARSs not only need to obtain users’ authorizations when accessing contextual data, but such systems require continuous feedback to refine recommendations. Yet, extant literature on user-system interactions in CARSs tend to be technological rather than psychological. Braunhofer et al. (2014) advocated a novel algorithmic preference elicitation method in CARSs to promote user-system interactions. Conversely, Santos et al. (2016) asserted that context-aware recommendations could be delivered in a more interactive fashion (e.g., recommending a nervous learner to breathe deeply by switching on a light). Departing from the technological aspects of CARSs, our research aims at investigating the psychological aspects of user-system interactions.

As mentioned earlier, many studies have proposed that compared to traditional recommender systems, CARSs could deliver more relevant recommendations that match users’ needs. There is however a gap in contemporary knowledge on how improved recommendations could be influenced psychologically through users’ interactions with CARSs. If we succeed in bridging this knowledge gap, we would be able to enrich all four research streams of CARSs and not merely for studies in the ‘fundamentals’ category.
**User-System Interactions and Cooperative Learning**

For user-system interactions, learning is pivotal in CARSs due to its complexity and enhanced interactivity (Adomavicius and Tuzhilin 2015). For recommender systems, users’ preference could be constructed during their interactions with the system via product learning (Amir and Levav 2008). Users could learn the way to best express their needs or preferences, to check system explanations and to compare recommendations (Komiak and Benbasat 2006).

Zhang et al. (2011) distinguished between two forms of learning whenever consumers shop online—consumer and retailer learning. According to Zhang et al. (2011), consumer learning is a “process whereby consumer knowledge is accumulated through repetitive purchase-related experiences” (p. 862). Similarly, retailer learning refers to a “process whereby retailers accumulate knowledge about individual customers through repetitive interactions”. (p. 863). Apart from consumer and retailer learning, we hold the view that there exists another form of learning for CARSs: cooperative learning. As noted by Kettinger and Lee (2005), two levels of service quality exist for information systems: desired service and adequate service. In general, static preferences are easy to collect and interpret, therefore conventional recommender systems could attain ‘desired service’ quality levels effortlessly. But the same cannot be said for CARSs. Due to the dynamic and sophisticated nature of contextual preferences, there is a greater likelihood for CARSs to provide mismatched recommendations. We therefore purport that cooperative learning plays an instrumental role in user-system interactions within CARSs because it is only through cooperative learning that user-system interactions can, at the very least, meet ‘adequate’ levels of service performance as indicated by Kettinger and Lee (2005). Building on the work of Zhang et al. (2011), we define **cooperative learning** as a process whereby consumer cooperate with the system to accumulate knowledge about themselves through repetitive interactions.

From users’ perspective, they are willing to cooperate with the system to know how the system works. Specifically, after incorporating contextual information into the recommendation process, the system could better anticipate users’ needs and hence, recommendations could automatically adjust to match users’ context. For instance, if a person lives in Beijing and then visits Shanghai on business, he/she would receive recommendations for restaurants in Shanghai when opening a context-aware restaurant recommender system without having the need to alter any setting. However, under certain circumstances, rules of recommendations are not necessarily obvious. Only after realizing how the system learns, users could make their decisions about how to utilize recommendations. Conversely, from the standpoint of recommender systems, they require responses from users to interpret a diverse range of contextual information. For systems that have to orchestrate data from multiple sources like sensors, third party applications, or user profiles, it is hard to interpret these data without deciphering the associations between users’ behavior and their situated context. For example, if a system were to capture a context like “location=meeting room, activity=sitting, company=several persons”, the system could not conclude that the user is attending a meeting because they could also be having lunch with colleagues after a meeting. For this reason, to better comprehend a great deal of raw sensor data, the system would need to obtain users’ cooperation (e.g. more detailed preference or feedback, positive authorizations). Otherwise, it will be difficult for the system to figure out which attributes are salient and why. Besides, conflicting contextual information could be elicited by the system. GPS could indicate you are at home at the moment while the calendar shows you are supposed to be attending a meeting in the office, which will be difficult for the system to synthesize (Perera et al. 2014).

Collectively, cooperative learning is especially important for CARSs when incorporating distinct sources of contextual information. Likewise, Yurur et al. (2016) claimed that the idea behind context-aware computing is to “encourage users to collect, analyze and share local sensory knowledge in the purpose for a large scale community use by creating a smart network” (p. 68).

**Social Interdependence Theory**

Social Interdependence Theory (SIT) (Johnson and Johnson 1989) is often applied to comprehend cooperative learning in the fields of business and education (Janssen et al. 1999; Johnson and Johnson 2002; Johnson and Johnson 2009). According to the SIT, cooperation is derived from positive interdependence among goals, meaning that an individual’s actions could facilitate goal achievement for himself/herself and others simultaneously (Johnson and Johnson, 2002). In this sense, SIT consists of
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three focal components: social interdependence, interaction patterns, and outcomes (Johnson and Johnson 2009), which we contextualized as positive interdependence, promotive interaction and cooperative learning outcomes in this research. From the viewpoint of social interdependence, we argue that it is vital for CARSs to deliver desirable outcomes in the form of cooperative decision quality, affective acceptance and error tolerance. The purpose of a recommender system is to provide appropriate recommendations and reduce information overload for users. As a consequence, how users evaluate the recommendation results from both cognitive and affective angles constitute essential outcomes. Besides, given the traits of context-aware computing (i.e. high likelihood of providing mismatched recommendations), we must also factor in users’ error tolerance.

Even though past studies tend to examine positive interdependence in human-human relationships, we contend that social interdependence could also apply to human-system relationships. We define positive interdependence in CARSs as users’ perceptions of the extent to which they share a common goal with the CARS in generating recommendations that best match their needs. Furthermore, we contextualize promotive interaction to the domain of CARSs by defining it as users’ perceptions of the extent to which they had taken actions to facilitate goal attainment for CARSs.

Positive interdependence enables users to recognize the merits of learning from others in the organization (Janz and Prasarnphanich 2003). Likewise, high level of positive interdependence will prompt users to feel that they could not be exposed to appropriate recommendations without cooperating with CARSs to share knowledge, which is deemed to be critical in goal attainment. Whenever the system offers suitable recommendations based on users’ sharing of pertinent knowledge, it may compel users to feel that they have an obligation to reciprocate. Consistent with prior research (Pee et al. 2010; Janssen et al. 1999), if users perceived that CARSs exist to facilitate the achievement of their goal, they are more inclined to develop positive attitude toward such systems and undertake actions to contribute to the provision of better recommendations. We hence hypothesize that:

**Hypothesis 1:** Users’ positive interdependence will positively influence the level of their promotive interaction with context-aware recommender systems.

Outcomes of cooperative learning can be delineated into three types: effort to achieve mutual goals, positive interpersonal relationships, and psychological health (Johnson and Johnson 2005). In the same vein, we maintain that cooperative learning outcomes in CARSs take the form of users’ cooperative decision quality, affective acceptance, and error tolerance. Cooperative decision quality refers to users’ perceptions of the suitability of the recommendations after cooperating with CARSs. Affective acceptance refers to user’s perceptions of the extent to which they maintain agreeable relationships with CARSs whereas error tolerance refers to users’ perceptions of the extent to which they could bear the provision of mismatched recommendations by such systems.

Particularly, the achievement of mutual goals, in the context of CARSs, denotes the degree to which collaborative learning is able to optimize the effort expended by users in interacting with such recommender systems to boost decision quality. Undoubtedly, users must exert more effort to achieve their goals in a cooperative learning process. Nevertheless, users could gradually economize on their personal effort after each round of cooperation learning even though such improvements could prove imperceptible to them. In CARSs, the mutual goal between systems and users stems from the generation of recommendations that best match the latter’s needs. It is therefore easier for users to evaluate the relevance of recommendations, which in turn drives their decision quality. Positive interpersonal relationships always measure individual’s affective attitudes towards cooperating partners (Janssen et al. 1999). By extension, affective acceptance can be construed as an appropriate gauge of users’ attitudes towards CARS after cooperation. As for error tolerance, we treat it as another form of psychological health. According to Johnson and Johnson (2005), cooperation is positively associated with different kinds of psychological health, such as optimism about people, well-adjusted social relations and/or ability to cope with adversity. When encountering errors in CARSs, users’ ability to adjust their relationships with such systems psychologically becomes pivotal. Due to their complexity, it is not uncommon for CARSs to provide unsatisfactory recommendations because of misinterpreting contextual information and/or user behavior. Consequently, it is imperative for users to tolerant errors, which in turn, could beneficial to their long-term relationships (Cheverst et al. 2005). The preceding three outcome dimensions thus reflect focal considerations in users’ evaluation of user-system interactions in CARSs that deviate from mere
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recommendation metrics (e.g., perceptions of accuracy and novelty). Next, we hypothesize the relationships between promotive interaction and three outcomes.

Cooperation among individuals translates into an assimilation of diverse ideas and arguments, which could extend beyond each individual’s proposals. For example, Chen and Huang (2007) demonstrated that coordination among organizational members positively influences knowledge management in terms of knowledge sharing and application. The same can be said for the cooperation between CARSs and users. When a user engages in a promotive interaction pattern, they would proactively provide CARSs with more purposeful and targeted knowledge (e.g., detailed personal information and feedback towards recommendations). This in turn would allow CARSs to generate more reliable recommendations as compared to traditional recommender systems, thereby culminating in cooperative decision quality. In other words, users are more likely to find such recommendations useful due to stronger association with their current situation. We hence hypothesize that:

**Hypothesis 2:** Users’ promotive interaction will positively influence the cooperative decision quality of context-aware recommender systems.

Knowledge sharing in virtual communities could yield emotional benefits, like gratification from helping others and a boost to the self-esteem (Ardichvili 2008). Conceivably, knowledge sharing between systems and users may also bring about emotional effects in CARSs. CARSs are designed to unobtrusively deliver the right recommendations in a right way, at a right time, in the right place. The interaction in traditional recommender is always happening in the ‘Foreground’ (e.g., users have to enter their preference into the input boxes) whereas the same interaction occurs in the ‘Background’ for CARSs (Svanæs 2001). For example, a tourism application could dynamically recommend routes to visitors according to their movement trajectory. In other words, the higher the level of promotive interaction, the greater the willingness of users to contribute to the improved performance of CARSs and appreciate the role such systems play in the decision-making process. At the same time, promotive interaction implies more interactions with the CARS, thus culminating in greater system familiarity and higher affective acceptance psychologically. In the context of organizations, when an employee has a positive attitude towards his/her performance, he/she is more likely to have positive feelings that serve as a ‘self-reward’ (Janz et al. 1997). Likewise, users would have positive feelings towards CARSs if they were able to deliver affirmative performance. We hence hypothesize that:

**Hypothesis 3:** Users’ promotive interaction will positively influence their affective acceptance of context-aware recommender systems.

Because it is difficult to interpret the relationships between distinct contexts and user behaviors, users may at times be confronted with mismatched recommendations from CARSs, especially when these systems are proactive in their recommendations. Having a high level of promotive interaction suggests that users possess positive disposition towards their interactions with the CARSs (Johnson and Johnson 1989). In turn, it stimulates users to embrace the operating philosophy of these systems and exercise tolerance even when they happen to receive mismatch recommendations: they are aware that once feedback is offered, the recommendations could be corrected. Vogt (1997) suggested that cooperative learning has a positive effect in boosting tolerance among individuals to mistakes during the learning process. We hence hypothesize that:

**Hypothesis 4:** Users’ promotive interaction will positively influence their error tolerance towards context-aware recommender systems.

**Scrutability Features**

According to Cheverst et al. (2005), scrutability refers to “the ability of a user to interrogate her user model in order to understand the system’s behavior” (p. 236). Scrutability features are not limited to explanations like ‘tell me why the system did that button’; they also permit users to correct system assumptions (Pu et al. 2012, p. 342). For example, to make the recommendations more scrutable in a mobile tourist application, Setten et al. (2004) advocated features like giving users the option to decide to recommend items based on their interests and location but with options to not include information from the last visit. Scrutability features are vital in CARSs to make allowances for inherent mismatches between how CARSs represent the world and how users perceive the world. For example, a CARS could recommend music in a running mode according to a user’s stride frequency. When the stride frequency is increasing, it
might recommend happy music. Yet, certain users may enjoy soft music under such circumstances. For these users, they would prefer the option to modify the way reality is modeled in the CARS and this could be accomplished through scrutability features.

We posit that scrutability features could moderate the relationships between promotive interaction and cooperative learning outcomes. Explanations of CARSs’ rationale is likely to give users a sense of control and could lead to more positive attitudes towards such systems. Also, emphasizing users’ role in the recommendation process could help to promote self-awareness (Kay 2006), thereby encouraging users to be more active in cooperating with CARSs. Scrutability features might also enable users to correct incorrect assumptions contained in the way reality is modeled in CARSs, thereby amplifying users’ ability to anticipate recommendations. Due to the anticipation, users might be less tolerant upon encountering mismatched recommendations. We hence hypothesize that:

**Hypothesis 5**: Scrutability features of context-aware recommender systems will reinforce the positive relationship between users’ promotive interaction and the cooperative decision quality of such systems.

**Hypothesis 6**: Scrutability features of context-aware recommender systems will reinforce the positive relationship between users’ promotive interaction and their affective acceptance of such systems.

**Hypothesis 7**: Scrutability features of context-aware recommender systems will attenuate the positive relationship between users’ promotive interaction and their error tolerance towards such systems.

Figure 1 depicts our proposed theoretical model of cooperative learning in CARSs. Specifically, we posit cooperative decision quality, affective acceptance, and error tolerance as cooperative learning outcomes (or dependent variables) that are affected by the antecedent (or independent variable) of positive interdependence. In addition, we postulate promotive interaction as a mediator between positive interdependence and cooperative learning outcomes whereas scrutability moderates the relationships between promotive interaction and cooperative learning outcomes.

**Methodology**

To validate our theoretical model of cooperative learning in CARSs, we plan to employ a mixed methods approach that includes both a survey and a within-subject experiment involving functional magnetic resonance imaging (fMRI). Data collected via the survey could validate our proposed research model whereas neuroscience would serve to illuminate the psychological mechanisms underpinning hypothesized relationships.

For the survey, subjects would be recruited from online crowd-sourcing platforms in China. The reason for choosing Chinese subjects is the popularity of location-based services in China. According to MMA (2009),
Countries in Asia Pacific (APAC) are often at the forefront of mobile technology. Since China has high urban density and a massive population of mobile users, it is amenable for investigating the performance of CARSs. Measurements for positive interdependence, affective acceptance and cooperation decision quality will be adapted from Janssen et al. (1999), and those for error tolerance from Cheverst et al. (2005). Conversely, items for promotive interaction will be self-developed and conform to standard psychometric procedures (Moore and Benbasat 1991). At the onset of the online questionnaire, subjects have to identify a familiar CARS, and then answer the questions in the survey instrument. In order to assess the content validity of the items, we follow the procedures outlined by Mackenzie et al. (2011). We will recruit college and doctoral students to rate the extent to which measurement items in the survey instrument reflect the latent constructs in our research model. To assess inter-rater reliabilities, we will measure the degree of agreement in classifying items for each pair of raters. As for model testing, we may opt for Smart PLS as a tool to validate both the measurement model and the structural model. Item reliability, internal consistency, convergent, and discriminate validity would be assessed in the measurement model while path coefficients and their significance would be evaluated in the structural model.

A single survey has several shortcomings due to its retrospective nature. Respondents’ self-assessment could lead to unintended biases. Furthermore, surveys could not detect causality. Therefore, to gain an in-depth appreciation of the psychological mechanisms underlying cooperative learning, we would extend our research through conducting within-subject fMRI experiments. These experiments serve two primary purposes. The first is to investigate whether CARSs could culminate in perspective taking. The secondary objective is to validate the effects of scrutability features in CARSs. Using a PET experiment, Ruby and Decety (2001) observed that a third-person perspective, as opposed to a first-person one, could stimulate special brain areas like right inferior parietal lobe, precuneus and somatosensory cortex. We argue that the detection of an increased level of activity in these specific brain areas when users are interacting with CARSs, are likely to be correlated to the psychological mechanism underpinning cooperative learning (i.e., perspective taking).

Similar to the majority of fMRI studies, we will recruit students as participants who are familiar with mobile technologies and CARSs. Before coming to the fMRI scanner, we will illustrate what a CARS is and then asked the participants to choose a familiar CARS. After that, each participant will be presented various statements or image in the scanner. According to Dimoka (2012), there are two kinds of trial designs in an fMRI study: “blocked (fixed sequential order of presentation of the experimental conditions using extended time intervals) and event-related (randomized order of the presentation of experimental conditions in relatively short time intervals)” (p.819). We choose event-related trail design because it is our objective to measure distinct experimental conditions, which includes neutral statement, contextual statement, positive interdependence measurement, promotive interaction measurement, cooperative decision quality measurement, affective acceptance measurement, error tolerance measurement, interface with scrutability features, and interface without scrutability feature. Neutral statements indicate how recommender systems are working (e.g. a recommender system provides relevant recommendations) while contextual statements draw attention to features of context-aware computing (e.g. a context-aware recommender system refines recommendations according to your preferences.) while contextual statements draw attention to features of context-aware computing (e.g. a context-aware recommender system refines recommendations according to your context).

**Expected Contribution to Theory and Practice**

Prior research on CARSs tends to focus on technical issues, thereby culminating in a knowledge gap in comprehending how such systems function from a user-system interaction perspective. To this end, we advance a research model to shed light on how user-system interactions could contribute to the performances of CARSs. In doing so, our study extends the SIT beyond inter-human relationships to the context of human-machine relationships, thereby offering a novel theoretical perspective to better inform the design of CARSs. Given that a survey cannot fully validate our conceptual logic, we hope to uncover the underlying psychological mechanisms through well-designed fMRI experimental studies. Conceivably, we will also contribute to methodological insights for conducting fMRI studies in the context of CARSs.

Apart from the theoretical implications, we expect that our research to also provide pragmatic value. Considering the growing interest in CARSs, it is necessary for us to improve the performance of such systems through features like scrutability, which would necessitate further inquiry. Empirical findings
from our study could contribute to the interface design of context awareness features to improve the performance of CARSs.

Conclusions

This research seeks to arrive at a deeper understanding of performance of CARSs from a user-system interaction angle. By constructing a research model from a cooperative learning viewpoint, we endeavor to illustrate that positive interdependence could affect promotive interaction, which in turn, shapes the performance of CARSs. We further strive to validate our model through a combination of surveys and fMRI experiments. In doing so, we hope to unravel the psychological mechanisms underlying human-machine relationships in the context of CARSs.

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