# The Effect of Recommender Systems on Users' Situation Awareness and Actions

*Research-in-Progress* 

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#### Abstract

Many organizations are implementing recommender systems with the expectation to influence users' actions. However, research has shown that poorly designed recommender systems may be counterproductive. For instance, if a recommender system provides too many recommendations, users cannot focus on relevant recommendations anymore. Therefore, recommender systems need to be balanced and adjusted to the processes in which they shall support users. Only designed correctly, recommender systems may influence users' situation awareness and, ultimately, enable them to perform informed actions.

Research has shown that users' situation awareness depends on users' elaboration. Therefore, we draw on the Elaboration Likelihood Model to conceptualize recommendation velocity and recommendation faithfulness as two variables that influence users' situation awareness. Furthermore, since research identified process automation as a major antecedent of situation awareness, we conceptualize process automation as a third influencing variable. Finally, we develop a conceptual research model and outline our intended validation and expected contributions.

**Keywords:** Recommender system, intelligent agent, user behavior, situation awareness, elaboration likelihood model.

# Introduction

The large number of products available on the internet have given rise to a need for recommender systems that assist users in their decision making (Xu et al. 2014). For instance, product recommender systems assist consumers in choosing the "right" products (Ricci and Werthner 2006; Xu et al. 2014). Through aggregating and analyzing data about the current user and linking it with the user's own historical and/or other users' historical data, recommender systems assist users through suggesting content, products or services (Adomavicius and Tuzhilin 2005; Park et al. 2012). However, research has shown that recommender systems may quickly become annoying and users may stop following them (Bevan et al. 2012; De Voe 2009; Matook et al. 2015). Only properly designed recommender systems hold their promises of assisting users (Gretzel and Fesenmaier 2006; Gretzel 2011; Leavitt 2006; Xu et al. 2014). To better understand the situations under which recommender systems are beneficial, multiple scholars called for an investigation of factors that influence the impact of recommender systems (Arazy et al. 2010) and cause users to act upon the invoked recommendations (Li and Karahanna 2015; Matook et al. 2015).

As soon as users elaborate on recommendations, recommendations may become influential and may persuade users to perform specific actions (Yoo et al. 2013). By adopting the Elaboration Likelihood Model (ELM; Petty and Cacioppo 1986a, 1986b), information systems (IS) scholars started investigating how users engage in cognitive elaboration when using IS. E.g., IS scholars confirmed the existence of two distinct cognitive processes and identified cues for both types of cognitive processing, i.e., controlled processing (with cues such as argument quality, information quality) and automatic processing (with cues such as source credibility, trust) (Angst and Agarwal 2009; Bhattacherjee and Sanford 2006; Yang et al. 2006; Zhou 2012). Furthermore, IS researchers showed that users differ regarding their need for cognition. Users with high needs for cognition are more likely to carefully elaborate their behavior should be provided with differently personalized recommendations (Ho and Bodoff 2014; Tam and Ho 2005).

Furthermore, research has shown that elaboration shapes users' situation awareness, i.e. their knowledge about "what is going on" (Endsley 1995a, p. 36). This is important, because situation awareness mediates the impact of information provided to users on users' decision making and actions (Endsley 1995a). However, although extant literature studied the impact of recommender systems (e.g., Gretzel 2011; Jabr and Zheng 2014) as well as the impact of elaboration on individuals' situation awareness (e.g., Alfredson 2007; Endsley 1996; Seebach et al. 2011) separately, to the best of our knowledge, no study vet examined how the two interact with each other to influence users' actions. In order to address this gap, we conceptualize elaboration of recommendations as an antecedent for users' situation awareness and, ultimately, for their actions. Besides, we also conceptualize three different moderators that determine how elaboration of recommendations influences situation awareness. Following extant elaboration research, we conceptualize *recommendation faithfulness* as a cure for controlled processing and *recommendation* velocity as a cue for automatic processing (Gawronski and Creighton 2013; Petty and Cacioppo 1986a; 1986b). Besides, we also conceptualize process automation as one characteristic of the user's activities that may influence the impact of a recommender system because process automation has been identified as a major antecedent for users' situation awareness (Endslev 1996). To summarize our objective in one guiding research question, our work addresses the following two research questions: How does elaboration on recommendations impact users' situation awareness and actions? How is this impact influenced by recommendation velocity, recommendation faithfulness and process automation?

We establish a research project to tackle this question. In particular, in this article we define and explain the aforementioned concepts and develop hypotheses. The remainder of this article is structured as follows. Section 2 introduces the Elaboration Likelihood Model as theoretical foundation for our work. Section 3 develops the concepts and section 4 introduces and explains our hypotheses. Finally, section 5 illustrates next steps and the data with which we intend to confirm/reject the hypotheses.

# **Elaboration Likelihood Model**

Research in social cognition has suggested a class of theories that are generically described as dualprocess theories (Chaiken and Trope 1999). The defining characteristic of these theories is that they divide the mental processes underlying social judgments and behavior into two general classes depending on whether they operate automatically or in a controlled fashion (Gawronski and Creighton 2013; Posner and Snyder 1975; Shiffrin and Schneider 1977). In social cognition, *automatic processes* meet at least one of the following four conditions: (1) they are elicited unintentionally, (2) they require few cognitive resources, (3) they cannot be stopped voluntarily, or (4) they occur outside of conscious awareness (Bargh 1994; Moors and De Houwer 2006; Gawronski and Creighton 2013). Conversely, processes that meet none of the four criteria are characterized as *controlled processes* (Gawronski and Creighton 2013).

One popular dual process theory that has been widely adopted by IS scholars, is the Elaboration Likelihood Model (ELM). The central notion of Petty and Cacioppo's (1986a; 1986b) ELM) is that attitude and behavior changes occur along an elaboration continuum whereby beliefs are primarily determined by how motivated and able individuals are to engage in effortful information processing. The model theorizes that the higher an individual's cognitive elaboration is, the more likely the individual is to process all object-relevant information. At the high end of the elaboration continuum, people assess all of the available object-relevant information (e.g., quality of the presented arguments) and integrate this information with their stored knowledge in order to obtain a carefully considered (although not necessarily unbiased) evaluation (Gawronski and Creighton 2013). The act of assessing objects and events with high elaboration is a *controlled process* because (1) it is elicited intentionally, (2) requires relatively high cognitive resources, (3) can be stopped voluntarily, and (4) requires conscious awareness (Gawronski and Creighton 2013). Conversely, at the low end of the elaboration continuum, people engage in considerably less scrutiny of object-relevant information. When elaboration is low, evaluations of objects and events can be effected from a cursory examination of the available information (e.g., by examining only a subset of the available information) or by the use of heuristics and other types of information processing short-cuts (e.g., "I agree with people I like"). Thus, the act of assessing objects and events with low elaboration is an *automatic process* (Gawronski and Creighton 2013).

# **Conceptual Development**

**Elaboration of Recommendations.** Our work focuses on recommender systems that assist users but do not necessarily enforce predefined activities. As implied in the word *recommender*, a recommender system *proposes* a specific activity or a set of alternate activities to the user. For instance, a navigation system such as GoogleMaps proposes several alternative routes to a user. The user can then select a subset of routes (e.g., only public transport or only toll-free routes) and gets an adjusted subset of the initially recommended routes. Thus, there is no enforcement of a particular route.

Since recommender systems leave making judgments and decisions to the user (Yoo et al. 2013), we differentiate recommender systems from systems that guide users along specific processes and, thereby, enforce those processes. An example for such an "enforcement system" would be a system that, if a manager hires a new employee, displays the required activities for receiving a security clearance for the new hire. In this case, the system would not actually recommend activities but rather represent a "to-do list" (Morana et al. 2014). This differentiation sets the boundaries around the applicability of our work.

In particular, we assume that only if users elaborate on recommendations, these recommendations may become influential (Li and Karahanna 2015; Matook et al. 2015). However, not all recommender systems demand the same amount of cognitive effort. For instance, a car navigation system may propose alternate routes from which the user simply may select the one that leads through the most interesting neighborhoods and countryside. This requires the user to invest rather little cognitive effort. Conversely, an air-traffic control system may propose alternate routes for multiple aircrafts. This situation would require much more cognitive effort because the user (i.e., the air-traffic controller) would have to cognitively link, e.g., proposed routes with the aircrafts' remaining gas levels. Therefore, we conceptualize the extent to which a user engages in cognitively processing the recommendations that are proposed by a system as *Elaboration of Recommendations* (EoR). Building on our research question, we model EoR as the main independent variable in our study. However, this shall not argue that there are no important antecedents to EoR. In fact, especially characteristics of activities such as relevance are potentially confounding factors that may influence users' elaboration of activity recommendations. Therefore, we adopt *Task Characteristics* (Goodhue 1995) as a variable that should be controlled when examining EoR.

**Situation Awareness.** *Situation awareness* (SA) describes an actor's knowledge about a specific situation. In her seminal work, Endsley (1995a) distinguished three levels of an actor's situation awareness. First, on the most fundamental level, an actor has mere knowledge about the objects and

events in his or her environment. This level is referred to as *perception*. On the second level, i.e., *comprehension*, the actor has a certain understanding of the meanings of the objects and elements in his or her environment. Finally, on the third level, i.e., *projection*, the actor anticipates the future characteristics, status and dynamics of the objects and elements in his or her environment. Projection enables the actor to imagine and compare outcomes of possible behaviors and, thus, make rational decisions.

Although a sufficient perception of the environment is a necessary condition for an actor to understand his or her environment, it is not a sufficient condition. For instance, a student may visit a lecture about complexity of algorithms without any previous knowledge about algorithms. In this situation, it would be likely that the student gains a high perception of the lecture without gaining any understanding about the topic. Similarly, comprehension is a necessary condition for projection but not a sufficient one. For instance, stock traders may understand why prices for certain stocks recently went up or down. However, they might still not be able to reliably project future stock prices.

Recommendation Faithfulness and Recommendation Velocity. We define Recommendation Faithfulness (RF) as the extent to which the recommendation is semantically correct as it pragmatically needs to be (Burton-Jones and Grange 2013; Chandler 2002). RF represents an important characteristic of recommendations that should be processed in a controlled fashion according to the ELM. We use the notion of "faithfulness" because a recommender system should not only be judged based on its semantical correctness (which could be referred to as "recommendation accuracy") but also its pragmatic relevance (Li and Karahanna 2015; Yoo et al. 2013). For instance, a car navigation system that only bases its recommendations on semantics and not on pragmatism might propose the three fastest routes. However, a user may have only very little interest in the third fastest route because he or she would select the fastest or second fastest one. Thus, a recommender system which instead suggests a route that leads through nice neighborhoods and countryside might be more suited even if driving the road would take much longer. We chose RF as a characteristic of a recommendation because RF requires the user to engage in effortful, cognitive processing. Specifically, processing RF meets all four conditions for a cue that needs to be processed by the user in a controlled fashion (Gawronski and Creighton 2013): assessing RF is elicited intentionally (condition 1), requires relatively high cognitive resources (condition 2), can be stopped voluntarily (condition 3), and requires conscious awareness (condition 4).

Conversely, as an important characteristics of a recommendation that may be processed in an automatic fashion, we define *Recommendation Velocity* (RV) as the rate at which recommendations are changing. For instance, at the high end of the velocity continuum, buy and sell recommendations provided to stock market traders are outdated within seconds and, thus, need to be updated frequently. Conversely, on a lower level of the velocity continuum, routing recommendations provided by car navigation systems that lead users over straight long roads might be valid for several hours. In contrast to RF, processing RV does not require particularly high cognitive resources. Thus, RV represents a cue for automatic processing.

**Degree of Process Automation.** Besides studying characteristics of recommendations, we also investigate a characteristic of the process itself. In particular, we define the degree of process automation (PA) as the ratio of activities in a process that are not executed manually divided by the total number of activities in that process. This is consistent with Endsley (1996) who examined "level of automation" as influencing factor in her SA studies. In many cases the desired advantages and enhanced system functionalities which go well beyond human abilities could be achieved through automation (Endsley 1995a). Nevertheless, users still represent a crucial part in most automated systems. For instance, some systems are not able to properly deal with exceptional situations and cannot replace users' decision making. As a consequence, users need to perform actions that cannot be automated (Endsley 1996).

However, with regard to the overall process performance, this human-machine entanglement nourishes an "out-of-the-loop" performance problem (Endsley 1995a). As the degree of automation increases, users become unaware and laggard in identifying the occurrence of problems which require their intervention (Endsley 1996). As a consequence, if problems are recognized, additional time is required to understand the context and what is going on. This in turn limits timely mitigation of the problem (Endsley 1996).

**Informed Action.** In order for an individual to use an IS effectively, the IS needs to afford the individual to make informed actions (Burton-Jones and Grange 2013). Burton-Jones and Grange (2013) define

*Informed Action* (IA) as the degree to which the individual acts upon information provided by an IS which faithfully represents relevant situations. We adopt IA as the ultimate dependent variable in our model.

## Hypotheses

In this section, we present our hypothesized effects between the concepts introduced in the previous section: EoR, SA, RF, RV, PA, and IA. In particular, we differentiate between the three SA levels, i.e., perception (SA level 1), comprehension (SA level 2), and projection (SA level 3). To facilitate reading, we first present an illustration of the conceptual model in Figure 1 and then explain all hypothesized effects separately. Furthermore, we illustrate the influences of all hypothesized moderation effects in Figure 2.



As introduced above, the main independent variable in our study is EoR. In order to influence an individual user's behavior, the individual needs to process the recommendation. In consistence with Petty and Cacioppo's (1986a; 1986b) ELM, this processing occurs along an elaboration continuum ranging from "just" following the recommendation to carefully scrutinizing the recommendation before making a decision about following the recommendation or not (e.g., by considering alternative activities and their likely outcomes). The more an individual engages in thinking about a recommendation, the greater his or her perception and comprehension of the respective situation will become. Furthermore, the individual may better project the situation into the future if he or she deeply elaborates about future outcomes. Therefore, we hypothesize that EoR positively influences SA on all three levels.

Hypothesis 1. A user's elaboration of recommendations positively influences his or her situation awareness.

Hypothesis 1a. A user's elaboration of recommendations positively influences his or her situation perception (SA level 1).

Hypothesis 1b. A user's elaboration of recommendations positively influences his or her situation comprehension (SA level 2).

Hypothesis 1c. A user's elaboration of recommendations positively influences his or her situation projection (SA level 3).

Furthermore, we conceptualized RF as a characteristic of the invoked recommendations. Users may gain a better perception, situation comprehension and projection if the recommendation for this situation is faithful, i.e., accurate and relevant (Burton-Jones and Grange 2013; Li and Karahanna 2015). Furthermore, as explained in the previous section, faithfulness represents a characteristic of the recommendation that should be processed by the user in a controlled fashion. As such, the impact of RF benefits from users who deeply engage in elaboration of the recommendation (Gawronski and Creighton 2013). Specifically, the higher a user's cognitive elaboration is, the more the user's perception, comprehension and projection will benefit from the recommendation's faithfulness. Thus, we hypothesize that highly faithful recommendations strengthen the positive impact of users' EoR on their SA (H2a, H2b, H2c). Conversely, recommendations of low faithfulness (e.g., suboptimal or misleading recommendations) have a weaker positive or even a negative effect on the impact of EoR on SA.

In addition, we hypothesize that different SA levels gain different benefits from elaborating on faithful recommendations. Since understanding a situation only enables projecting the situation into the future but does not determine it, projecting the situation requires more elaboration than only understanding it (Endsley 1995a). Hence, the impact of a user's EoR on the user's situation projection (SA level 3) benefits stronger from highly faithful recommendations than the impact of a user's EoR on the user's situation comprehension of that situation (SA level 2). Analogous, the impact of a user's EoR on the user's situation comprehension (SA level 2) benefits stronger from highly faithful recommendations than the impact of a user's EoR on the user's situation comprehension (SA level 2) benefits stronger from highly faithful recommendations than the impact of a user's EoR on the user's situation endpetition (SA level 2) benefits stronger from highly faithful recommendations than the impact of a user's EoR on the user's situation endpetition (SA level 2) benefits stronger from highly faithful recommendations than the impact of a user's EoR on the user's situation endpetition (SA level 2) benefits stronger from highly faithful recommendations than the impact of a user's EoR on the user's perception of that situation (SA level 1) (Endsley 1995a). We formulate the hypothesized differences in these effects as Hypothesis 2d.

Hypothesis 2. The impact of a user's elaboration of recommendations on his or her situation awareness (H1), is positively influenced by the faithfulness of those recommendations.

Hypothesis 2a. The impact of a user's elaboration of recommendations on his or her situation perception (H1a), is positively influenced by the faithfulness of those recommendations.

Hypothesis 2b. The impact of a user's elaboration of recommendations on his or her situation comprehension (H1b), is positively influenced by the faithfulness of those recommendations.

Hypothesis 2c. The impact of a user's elaboration of recommendations on his or her situation projection (H1c), is positively influenced by the faithfulness of those recommendations.

Hypothesis 2d. *The moderation effect of H2c is stronger than the moderation effect of H2b. Also, the moderation effect of H2b is stronger than the moderation effect of H2a.* 

In contrast to RF, RV represents a characteristic of invoked recommendations that may be processed in an automatic fashion. RV refers to the pace at which recommendations are updated. Elaborating timely recommendations leads to greater SA than elaborating outdated recommendations because the more current a recommendation is, the more accurate knowledge about a specific situation it may cause (Wixom and Watson 2001). However, recommendations may also be updated too quickly. For instance, in a highly volatile environment such as stock market pricing, buy and sell recommendations are outdated and updated within seconds. Carefully scrutinizing a recommendation in such a situation would take longer than the time for which the recommendation is valid. This is consistent with cognitive research findings which indicate that intermediate levels of user engagement in a process cause greater SA and work performance than low and high levels of user engagement (Endsley 1987, Endsley and Kiris 1995). For instance, pilots report that if the automation degree in an aircraft reaches a certain point, they might start paying less attention. This in turn leads to an insufficient picture of the specific situation and, thus, causes an awareness problem (Endsley 1996).

As a consequence, we theorize that there exists a maximum degree of SA that depends on the pace at which recommendations are updated (i.e., RV) and the elaboration effort the individual invests (i.e., EoR). In other words, an individual's perception (H3a), comprehension (H3b), and projection (H3c) follow inverted U-shaped curves if EoR and RV increase. This is consistent with cognitive processing effects proclaimed by dual process theories such as ELM because the actor loses his or her ability to carefully think about recommended activities if recommendations are changing quickly. These hypothesized effects (H3a, H3b, H3c) are important for practitioners and scholars because they indicate that there exist optimal maximum levels of SA that can be reached. Realizing these maximum levels of SA requires adjusting the velocity at which recommendations are updated. If recommendations are updated

frequently, the user's SA reaches its' maximum level. However, if recommendations are updated too quickly, the user's situation comprehension and situation projection will decrease again.

Furthermore, since projecting a situation requires more elaboration than only understanding it (Endsley 1995a), projection is influenced more by limited time that users may invest in EoR than comprehension (H3d). Similarly, since understanding a situation requires more elaboration than only perceiving it (Endsley 1995a), comprehension is influenced more by less elaboration than perception (H3d).

Hypothesis 3. The impact of a user's elaboration of recommendations on his or her situation awareness (H1), is moderated by the velocity with which recommendations are updated.

Hypothesis 3a. The impact of a user's elaboration of recommendations on his or her situation perception (H1a), will follow an inverted U-shaped curve as recommendation velocity increases.

Hypothesis 3b. The impact of a user's elaboration of recommendations on his or her situation comprehension (H1b), will follow an inverted U-shaped curve as recommendation velocity increases.

Hypothesis 3c. The impact of a user's elaboration of recommendations on his or her situation projection (H1c), will follow an inverted U-shaped curve as recommendation velocity increases.

Hypothesis 3d. *The moderation effect of H3c is stronger than the moderation effect of H3b. Also, the moderation effect of H3b is stronger than the moderation effect of H3a.* 

Besides characteristics of the invoked recommendation that influence the impact of EoR, we propose the degree of PA as a characteristic of the overall process that influences the impact of EoR. Earlier studies showed that individuals' SA is lower in an automated process compared to a process in which all activities are conducted manually (Endsley and Kiris 1995). As a consequence, individuals who are performing activities of a process with little PA can rather leverage the positive impact of EoR on SA than individuals who are performing activities of a process that is highly automated, the individual's EoR will have a weaker positive influence on the individual's SA. This means that for a given situation, PA negatively influences the positive impact of EoR on the individual's situation perception (H4a), situation comprehension (H4b), and situation projection (H4c).

Again, we hypothesize that the moderation effect differs depending on the investigated SA level. Since projecting a situation requires more elaboration than only understanding it (Endsley 1995a), projection is influenced more by the negative influence of PA on the impact of EoR (H4d). Similarly, since understanding a situation requires more elaboration than only perceiving it (Endsley 1995a), comprehension is influenced more by the negative influence of PA on the impact of EoR (H4d).

Hypothesis 4. The impact of a user's elaboration of recommendations on his or her situation awareness (H1), is negatively influenced by the degree to which the overall process is automated.

Hypothesis 4a. The impact of a user's elaboration of recommendations on his or her situation perception (H1a), is negatively influenced by the degree to which the overall process is automated.

Hypothesis 4b. The impact of a user's elaboration of recommendations on his or her situation comprehension (H1b), is negatively influenced by the degree to which the overall process is automated.

Hypothesis 4c. The impact of a user's elaboration of recommendations on his or her situation projection (H1c), is negatively influenced by the degree to which the overall process is automated.

Hypothesis 4d. *The moderation effect of H4c is stronger than the moderation effect of H4b. Also, the moderation effect of H4b is stronger than the moderation effect of H4a.* 

Overall, we suggest three moderation effects between EoR and RF on SA (H2a, H2b, H2c), three moderation effects between EoR and RV on SA (H3a, H3b, H3c), and three moderation effects between EoR and PA on SA (H4a, H4b, H4c). We visualize all nine moderation effects using common twodimensional interaction diagrams in Figure 2. In particular, the top row illustrates the moderation effects on perception (SA level 1), the middle row illustrates the moderation effects on comprehension (SA level 2), and the bottom row visualizes the moderation effects on projection (SA level 3).



We selected IA as dependent variable in our study. IA describes the extent to which a user acts upon the faithful representations he or she obtains from the IS (Burton-Jones and Grange 2013). We hypothesize that all three SA levels positively influence IA.

Hypothesis 5. A user's situation awareness (i.e., situation perception, situation comprehension and situation projection) positively influences his or her ability to make informed actions.

# **Intended Validation of the Model**

We are currently developing a recommender system that shall be assessed in three evaluation rounds analyzing each moderation effect in one individual setup. In a first round, different levels of recommendation velocity will be tested in a controlled lab experiment. For instance, we hypothesized that a user's awareness follows an inverted U-shaped curve if recommendation velocity interacts with the user's elaboration. This hypothesis is empirically testable in a controlled experiment by showing that a maximum degree of situation awareness exists if the recommendation velocity changes.

In a second round, we intend to extend a Business Intelligence system in a global bank with our recommender system. We will conduct a survey with users shortly before and again six months after extending the system and look for differences in the level of recommendation faithfulness (RF). Users may perceive, understand and project a situation better if the recommendation for a situation is faithful (i.e., accurate and relevant). This hypothesis is empirical testable by illustrating that a high level of RF promotes users with a deep engagement in elaboration of the recommendation on SA whereas misleading recommendations shall have a weaker positive or even a negative effect on the impact of EoR on SA.

In a third round, different levels of process automation (PA) will be tested in a controlled lab experiment. For instance, we hypothesized that a user's awareness follows a linear curve if PA interacts with the user's elaboration. This hypothesis is empirically testable in a controlled experiment by showing that a higher degree of situation awareness exists if the level of PA is low.

We acknowledge that measuring users' cognitive processes is a difficult task. Therefore, for the three evaluation rounds we will adopt the approach of Meservy et al. (2014). Specifically, we are planning to complement techniques that have been developed for measuring users' elaboration in the IS discipline such as surveys (e.g., Angst and Agarwal 2009; Bhattacherjee and Sanford 2006, Ho and Bodoff 2014) with techniques that are more frequently used in the Psychology and the Human-Computer Interaction discipline such as eye tracking (e.g., Goldberg and Kotval 1999; Just and Carpenter 1976; Loftus 1972).

Similarly, we intend to complement different techniques for measuring SA. For measuring SA on the individual user's level, literature recommends a mixture of self-rating techniques, freeze probe techniques, performance measures, and process indices (e.g., Salmon et al. 2006). Self-rating techniques are leveraged to assess subjective measurements of users' SA. The self-rating is usually executed post-trial, by providing a subjective assessment of users' perceived SA utilizing some sort of rating scales. Well-established scales for measuring SA are provided, e.g., by Taylor (1990). The advantages of this technique are its non-intrusive nature and ease of use.

In addition, freeze probe technique represent an objective measurement approach and provide direct online questions to assess SA during randomly "freezes" in the respective task simulation under analysis (Salmon et al. 2006). During such a "freeze" all windows and operational displays of the recommender are blanked. At the point of the freeze the user will have to answer a set of questions based on their momentary understanding of a situation. For instance, the Situation Awareness Global Assessment Technique (SAGAT) represents an established freeze probe procedure (Endsley 1995b). The advantage of this technique is its direct and objective nature which allow to "tap into" users' SA (Salmon et al. 2006).

These direct measures are corroborated by indirect performance measures that focus on outcomes. In particular, we intend to assess performance using users' time required to perform a task, the number and type of errors, and using a binary variables representing whether the user reached the expected outcome (Davenport and Short 1990). Finally, eye tracking allows us to define proficient process indices measures (Smolensky 1993). According devices tracks user's fixations on the displayed elements on the screen in order to indicate the extent to which such elements (e.g., a recommendation) have been processed.

# **Expected Contributions**

In the last decade, recommender systems researchers adopted a second perspective focusing on users in addition to the yet established perspective focusing on prediction accuracy. As McNee et al. (2006) noted, researchers first need to "create recommenders that can generate useful recommendation lists" (p. 2) through rethinking recommender systems from a user-centric perspective. Ever since, several scholars followed this approach. For instance, Adomavicius et al. (2013) showed that recommender systems may cause anchoring effects that manipulate consumer preferences whereas Knijnenburg et al. (2012) showed how user experience is shaped by recommender systems.

By focusing on how users process recommendations, our work applies such a perspective. We conceptualized elaboration of recommendations as antecedent for users' SA and, ultimately, users' actions. Drawing on elaboration research, we then introduced characteristics of the recommendation that affect the recommendation's impact differently. Furthermore, building on Endsley's (1996) studies on automation level, we conceptualized PA as a characteristic of the set of activities a user is performing that influences the impact of the invoked recommendations.

Overall, we believe that continuing the work outlined in this article will improve our understanding of how recommendation characteristics (e.g., recommendation faithfulness, recommendation velocity) and process characteristics (e.g., process automation) influence users' elaboration of recommendations and, thus, the impact of those recommendations. Gaining this understanding generates multiple benefits. For instance, understanding the influence of recommendation velocity on EoR may guide system designers to build more effective recommender systems that do not only focus on the accuracy of recommendations but also on the frequency at which recommendations should be "delivered" to users in order to maximize their awareness and support them in making informed decisions. Similarly, understanding the influence of process automation on EoR is valuable for system designers because in many exceptional situations users need to perform informed actions that cannot be automated. Finally, the influence of process automation on EoR also outlines a new research field at the intersection of process design, recommender system design and cognitive psychology (Gawronski and Creighton 2013).

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