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ORIGINAL ARTICLE

Extending the Technology Acceptance Model to assess automation

Mahtab Ghazizadeh · John D. Lee · Linda Ng Boyle

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Abstract Often joint human–automation performance depends on the factors influencing the operator's tendency to rely on and comply with automation. Although cognitive engineering (CE) researchers have studied automation acceptance as related to task–technology compatibility and human–technology coagency, information system (IS) researchers have evaluated user acceptance of technology, using the Technology Acceptance Model (TAM). The parallels between the two views suggest that the user acceptance perspective from the IS community can complement the human–automation interaction perspective from the CE community. TAM defines constructs that govern acceptance and provides a framework for evaluating a broad range of factors influencing technology acceptance and reliance. TAM is extensively used by IS researchers in various applications and it can be applied to assess the effect of trust and other factors on automation acceptance. Likewise, extensions to the TAM framework use the constructs of task–technology compatibility and past experience to extend its description of the role of human–automation interaction in automation adoption. We propose the Automation Acceptance Model (AAM) to draw upon the IS and CE perspectives and take into account the dynamic and multi-level nature of automation use, highlighting the influence of use on attitudes that complements the more common view that attitudes influence use.

Keywords Technology acceptance · Cognitive engineering · Trust in automation · Task–technology compatibility · Technology Acceptance Model (TAM) · Automation Acceptance Model (AAM)

M. Ghazizadeh · J. D. Lee
Department of Industrial and Systems Engineering, University of Wisconsin–Madison, Madison, WI, USA
e-mail: ghazizadeh@wisc.edu

J. D. Lee (✉)
3007 Mechanical Engineering, 1513 University Avenue, Madison, WI 53706-1572, USA
e-mail: jdlee@engr.wisc.edu

L. N. Boyle
Departments of Industrial and Systems Engineering, Civil and Environmental Engineering, University of Washington, Seattle, WA, USA
e-mail: linda@u.washington.edu

1 Introduction

The increasing capacity and ubiquity of technology makes the human–technology relationship an increasingly important part of daily life. In many cases, technology fundamentally changes a person's role, making system performance progressively dependent on the integrity of this relationship. Warning and control systems for cars, aircraft cockpit automation, algorithms that guide financial transactions, and even office applications are just a few of the increasingly automated technologies that touch life on a daily basis.

Automation has been defined as technology that executes a function that was previously performed by humans (Parasuraman and Riley 1997). By fully or partially carrying out functions previously accomplished by humans, automation becomes a complement to people in meeting task goals. However, automation rarely substitutes for the human: Automation does not simply replace the person and perform the tasks once performed by the person. Instead, automation changes the task structure, introducing new tasks and responsibilities, such as monitoring the automation and coordinating activities with the automation (Sarter et al. 1997). In fact, automation will not achieve its potential if not properly adopted by users and seamlessly integrated into a new task structure. The notion of *human–technology coagency* to describe the coupling between human and machine underscores this requirement (Hollnagel and Woods 2005).

Human–technology coagency describes a situation where both the human and the technological agent can initiate change and a highly coordinated interplay of human and automation activity is needed for effective operation. In this situation, high-performing automation is necessary, but insufficient for success. Automation must also be highly cooperative and enable the operator to rely on it appropriately. Appropriate reliance depends in part on how well the automation's interface and functionality support users in engaging and disengaging it (Kirlik 1993). Attitudes, such as trust and self-confidence, as well as workload and risk also play a critical role in mediating reliance (Lee and See 2004).

Two research communities, cognitive engineering (CE) and information systems (IS), have considered how attitudes toward technology influence reliance and use but have done so independently. The CE community has examined the compatibility between technology, task needs, and context as influencing users' acceptance of automation. They have shown that attitudes, such as trust in automation, play important roles in user reliance and acceptance (Lee and See 2004; Muir 1987). Inappropriate levels of trust can lead to automation misuse and disuse—corresponding to inappropriately high and low levels of reliance, respectively (Parasuraman and Riley 1997). Operators' trust and relationship with technology often progress through several stages as they adapt to a new system, from initial exposure to the innovation, to the adoption decision, and later to decision confirmation (Rogers 1995). As such, automation acceptance changes over time (Davis et al. 1989; Karahanna et al. 1999). In this context, the terms adoption and acceptance have similar meanings, but adoption has a slightly broader connotation. Adoption goes beyond acceptance to address patterns of reliance and dependence. These insights highlight the need for a dynamic model of automation adoption that considers short- and long-term use of automation.

The IS community has developed one of the most broadly used models of acceptance: Technology Acceptance Model (TAM) (Davis 1989; Davis et al. 1989). TAM posits that users' perceived usefulness and ease of use are the main determinants of their attitude toward a technology, which, in turn, predicts their behavioral intention to use and accept the system. TAM provides a general framework that describes factors affecting automation acceptance, such as task compatibility, experience, and mandatory usage. Such macro-level factors reflect broad job and organizational influences. TAM considers the effect of these macro-level factors as direct determinants of usage intentions and as they influence acceptance as mediated by perceptions of system usefulness and ease of use. In contrast, the CE community has examined the factors influencing users' beliefs and perceptions on a micro-level in terms of human–technology coagency. The micro-level acceptance dynamics become crucial in considering agent-like technology—people often interact with technology similarly to how they interact with each other (Reeves and Nass 1996).

This paper recommends an integrated framework for assessing automation adoption grounded in the micro-level concepts of human–technology coagency defined by the CE domain and the broader macro-level influences defined by the IS community in the TAM framework. This framework, termed Automation Acceptance Model (AAM), provides a more comprehensive perspective on automation reliance and acceptance.

2 Cognitive engineering perspective: implications of human–technology coagency for automation acceptance

Technological advancements have brought automation to many domains where it did not exist even a few years ago, such as advanced driver assistance systems (ADASs) for cars. While automation extends the human capabilities and relieves the operators of dangerous and demanding tasks, it can also have negative consequences, such as complacency, degraded situational awareness, deskilling, and mode confusion (Hollnagel and Woods 2005; Parasuraman and Riley 1997). The concepts of *coagency* and *joint cognitive systems* stress the need to consider the human–automation partnership as an adaptive goal-oriented system to respond to both expected and unexpected demands (Hollnagel and Woods 2005, 1983).

2.1 Task–technology compatibility and automation coagency

Automation is not a singular concept but varies across levels of automation (LOA) that range from fully manual (no automation) to fully automated control (Sheridan 1992; Sheridan and Verplank 1978). Systems that heavily restrict operators' behavior or those that force behavioral changes (high LOA) are less likely to be accepted when compared with nonrestrictive, informative systems (Van Der Laan et al. 1997). High LOAs can lead operators to rely on the automation when it fails (Parasuraman et al. 2000), whereas low LOAs can lead to poor performance when system demands exceed operators' capacity. Therefore, inappropriate LOA reflects poor task–technology compatibility, either when it exceeds the operator's desired level of system autonomy or when it falls short of the operator's needs.

A high LOA is needed when tasks exceed the capacity of the human to respond in a timely manner. For example, avoiding a rear-end collision may require a response time that is shorter than any drivers' reaction time, and so automation that has full authority to brake may be the only option to avoid collision. High LOA must consider who should maintain final authority: the operator or the automation. Granting automation full control without operator approval might be limited to situations where operators fail to respond or where operators cannot respond fast enough (Moray et al. 2000). Aside from the performance and safety implications of granting automation final authority, such design alternatives need to be evaluated in light of operator acceptance. Drivers are more accepting of collision warnings than automated control, which tends to be misunderstood, even when automated control performs better (Inagaki et al. 2007). Similarly, drivers tend not to accept lateral control assistance systems that use a motor cue (preactivation of the corrective gesture), even though such assistance is more effective than auditory warnings (Navarro et al. 2010; El Jaafari et al. 2008). These findings show that preference is not necessarily associated with performance, a notion previously emphasized by Bailey (1993) and Andre and Wickens (1995).

For enhanced safety and performance, the human operator should be coupled with the most competent technology. However, underestimating task complexity and overestimating performance predictability can lead designers to overestimate the competence of their technology. This failure to appreciate technological limits often leads to *brittle* automation or automation that fails unexpectedly because system designers overlooked some possible situations (Roth et al. 1987). Balancing automation authority with the moment-to-moment changes and the operators' ability to effectively respond represents a substantial challenge in supporting effective human–automation interaction. A promising approach for deciding the appropriate LOA is to adapt the automation to the situation and task context (Inagaki 2006). Automation *controllability* refers to the degree the operator can adjust the LOA (Flach et al. 1998), and *adaptive automation* refers to automation that dynamically switches authority between the human and the automation depending on the situation (Inagaki 2003; Scerbo 1996; Rouse 1988).

Higher LOA and adaptive automation can lead people to misunderstand the automation mode, causing *automation surprises* (Sarter et al. 1997). These surprises are well-documented with highly trained operators, such as aircraft pilots, and so are likely to be far more common where operators have less training, such as the typical driver. For ADASs and other such automations in daily life, surprises and conflicts need to be avoided to gain acceptance. To this end, a clear indication of the automation intent should be provided to the driver by designing automation that communicates this information in an effective and timely manner (Inagaki et al. 2008; Seppelt and Lee 2007). Alternatively, automation algorithms can be matched to the control strategies of the person and act in a manner consistent with how the person might act (Goodrich and Boer 2003; Sarter et al. 1997). If the automation's actions are comprehensible and the rationale for decision is transparent, the operators may view the automation more favorably, consistent with the notion of *observability* (Rogers 1995). Task–technology compatibility suggests that designers need to go beyond creating technically competent automation and match the automation design objectives to the task complexity, predictability, and criticality.

2.2 Dynamics of trust and reliance

Just as trust mediates relationships between people, people tend to rely more on automation they trust (Lee and Moray 1992, 1994; Parasuraman et al. 2008). According to Rotter (1980), trust is "a generalized expectancy held by an individual that the word, promise, oral, or written statement of another individual or group can be relied on" (p. 1). Trust is a social emotion that influences the interaction between people, consisting of three dimensions of predictability, dependability, and faith that evolve over time (Rempel et al. 1985). The evolution of trust in human–automation relationships can be described by the Extended Decision Field Theory that shows trust, self-confidence, and reliance vary according to a complex interplay between the changing attitudes and associated actions (Gao and Lee 2006).

Trust depends on the degree of experience with automation. A theoretical study on the effect of experience on trust posited that people initially base their trust on the automation's predictability, then with more experience, dependability dominates, and finally with long-term use, trust is driven by faith (Muir 1987). However, this ordering is not universal. In fact, the results of an empirical study that examined the effect of experience on trust showed that in the initial stage of interaction, faith rather than predictability accounted for trust (Muir and Moray 1996). The relative influence of predictability, dependability, and faith depends on the interplay of surface features (aesthetics, real-world feel, information structure) (Kim and Moon 1998; Fogg et al. 2001; Karvonen and Parkkinen 2001) and depth features (automation performance, observability, and controllability) (Lee and See 2004). Ideally, these factors will lead to levels of trust consistent with the true capability of the automation—to highly calibrated trust.

Poorly calibrated trust leads to automation misuse and disuse, corresponding to higher and lower than appropriate levels of reliance, respectively (Lee and See 2004). Overtrust (complacency) can also be an issue if the automation is highly but not perfectly reliable. These infrequent situations may impact the operator's ability to detect failures in the automation (Parasuraman et al. 2000). Therefore, automation should be designed to be both trustworthy—technically competent and matched to the task—and trustable—easily understood and transparent in its operation (Lee and See 2004).

Two major themes emerge from the CE community: task–technology compatibility and the need to design for coagency and the dynamics of trust and reliance. Compatibility of automation with the operator's expectations depends on system design and task context as well as the level of autonomy and authority granted to automation. Trust is determined by system performance and the quality of the operator's past interaction with the system. In considering these factors, CE researchers have mainly focused their attention on the short-term, micro-level observations of operator behavior. An extreme example is Gray and Boehm-Davis's (2000) description of micro-strategies, concluding that milliseconds matter when it comes to adopting new technologies. CE researchers mainly focus on the individual operators' behavior over short time periods, sometimes neglecting the more macro-level, longer-term considerations. Information systems (IS) research, on the other hand, consider macro-level interactions between the human and the technology, often captured by survey-based studies.

3 Information system perspective: Technology Acceptance Model and its extensions

The original TAM (Fig. 1) was built on the Theory of Reasoned Action of Fishbein and Ajzen (1975). TAM posits perceived usefulness (PU) and perceived ease of use (PEOU) as the main determinants of the attitude to use, which, in turn, predicts behavioral intention (BI) to use and actual system use (Davis et al. 1989). PU measures the degree that operators believe a technology will help perform a job, while PEOU measures the perceived utility of the effort to use the automation (Davis 1989). These TAM constructs demonstrate high reliability and validity and are robust to the measurement instrument design (Davis and Venkatesh 1996). As such, TAM has been used to assess user acceptance in a variety of domains, consistently explaining the variability in usage intentions and use behavior. TAM has demonstrated promise in providing quantitative measures of relationships between the external variables determining users' perceptions and the perceptions influencing attitudes and intentions. As such, many researchers have used this framework and have added new constructs and relationships to describe user acceptance (for examples, see Bajaj and Nidumolu 1998; Dishaw and Strong 1999; Gefen et al. 2003; Karahanna et al. 2006; Venkatesh and Davis 2000; Venkatesh et al. 2003; Yi et al. 2006).

The core constructs of the TAM model, PU and PEOU, are influenced by a number of external variables such as system features and user characteristics (Davis et al. 1989). Research to extend TAM has added new constructs beyond PU and PEOU that enhance the model's predictive power and has investigated how various external variables influence PU and PEOU. Some of these extensions are particularly complementary to CE research regarding automation acceptance.

The original TAM did not incorporate the influence of social and control factors. Taylor and Todd (1995) identified this shortcoming and augmented TAM by adding constructs from the Theory of Planned Behavior (TPB) (Ajzen 1991), such as subjective norms (a person's perception that most people important to him think he should/should not perform a behavior) and perceived behavioral control. These additions improved predictions of acceptance. On the basis of similar arguments, Yi et al. (2006) suggested constructs from TAM, TPB, and Innovation Diffusion Theory (IDT) (Rogers 1995). This model included three IDT constructs that improved prediction of BI: result demonstrability, image, and personal innovativeness. These findings demonstrate the value of considering personal and social factors surrounding technology adoption.

Another extension to TAM, TAM2, incorporated both social influence and cognitive instrumental processes (Venkatesh and Davis 2000). Social influence processes include subjective norms, voluntariness, and image (perceived status in one's social system). Cognitive instrumental processes include job relevance, output quality, result demonstrability, and PEOU. Another variation of TAM that offers a more complete account of acceptance than TAM2 is the Unified Theory of Acceptance and Use of Technology (UTAUT). This theory comprises of three direct determinants of BI (i.e., performance expectancy, effort expectancy, and social influence) and two direct determinants of use behavior (i.e., intention and facilitating conditions) (Venkatesh et al. 2003).

Another construct recently added to TAM is trust, which is of great interest to researchers in e-commerce and e-government because of the risk and uncertainty involved in the web-based environments. Trust in the e-vendor has been shown to determine intention to transact, both directly and indirectly through PU, PEOU, and perceived risk

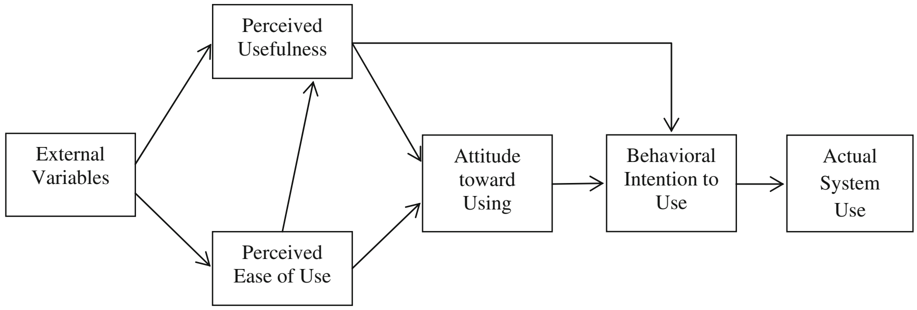

Fig. 1 Technology Acceptance Model (Davis et al. 1989)

(Pavlou 2003). Trust has also been considered as a direct determinant of BI, accounting for substantial variation in user adoption of e-government (Carter and Bélanger 2005). In these models, trust is typically defined in relation to the provider of technology and the channel of communication, more than the technology itself. This definition of trust is included in, but not synonymous with, the notion of trust in automation described in Sect. 2.2.

TAM asserts that external variables determine operator's PEOU and PU and therefore, indirectly influence user attitude and intentions. However, there is a diversity of approaches (Legris et al. 2003) with some researchers opting for no external variables in the model. For example, Venkatesh and Davis (2000) included seven variables (i.e., voluntariness, experience, subjective norm, image, job relevance, output quality, and result demonstrability) as external variables in TAM2, whereas Bajaj and Nidumolu (1998) considered no external variables. Other external variables of particular relevance to automation acceptance include the following: compatibility between task and technology, experience with the technology, and mandatory and discretionary technology use, as described later.

3.1 Compatibility between task and technology

Task–technology compatibility is a major determinant of automation acceptance in the CE literature (see Sect. 2.1) but is also emphasized by the IS community. Compatibility reflects the match among the operator, the technology, the task to perform, and the situation (Karahanna et al. 2006). More specifically, compatibility measures a technology's consistency with users' values, past experience, and needs (Rogers 1995). Compatibility is one of the five subjective characteristics of an innovation according to IDT and is captured through the job relevance and facilitating conditions constructs in some TAM-based models (Rogers 1995; Venkatesh and Davis 2000; Venkatesh et al. 2003).

Incorporating the Task–Technology Fit model constructs (Goodhue and Thompson 1995) into TAM enhanced the predictions of use (Dishaw and Strong 1999). Another TAM-based model considered task–technology compatibility at a higher degree of granularity, using four separate dimensions of compatibility (compatibility with preferred work style, compatibility with existing work practices, compatibility with prior experience, and compatibility with values) and showed causal linkages among the four dimensions of compatibility and also between compatibility beliefs and PU and PEOU (Karahanna et al. 2006).

3.2 Experience with the technology

The match between system attributes and user's past experience is an important task compatibility dimension (Rogers 1995). Experience with a specific technology is often associated with greater use of that technology (Guinan et al. 2010; Thompson et al. 1994). In a recent study, Kim and Malhotra (2005) examined the effect of past use on user attitudes and behaviors and found that past use positively influences PU and PEOU, as well as BI and actual usage, suggesting that automatic processes, as opposed to conscious decision making, play an important role in continued use. The positive influence of prior use on PEOU and BI has been confirmed by other studies (e.g., Bajaj and Nidumolu 1998; Dishaw and Strong 1999; Jackson et al. 1997), whereas the results regarding the influence of prior use on PU are inconsistent, with some studies finding a positive effect (e.g., Dishaw and Strong 1999) and others showing no effect (e.g., Jackson et al. 1997). Such inconsistencies suggest that the influence of prior use may depend on the particular technology and task characteristics, which merits particular attention as automation moves into everyday applications, such as ADASs in cars.

Experience with a system will shift the influence from social information toward personal judgment (Venkatesh and Davis 2000). This finding is consistent with the tendency for social norms to determine pre-adoption intentions, whereas attitudes determine post-adoption (Karahanna et al. 1999). Experience with a system also influences PEOU. With experience, specific user–system interaction characteristics, such as objective measures of system usability and perceived enjoyment, become more important in shaping user's perception of how easy the system is to use, although user's general perception of computer systems may still remain more influential (Venkatesh 2000). Experience also moderates the effect of determinants of BI, with effort expectancy being a stronger factor in early stages of experience and facilitating conditions becoming stronger in later stages of experience (Venkatesh et al. 2003).

3.3 Mandatory and discretionary use of technology

Compared with the CE community, the IS community has adopted a greater focus on mandatory and discretionary use. The distinction between mandatory and discretionary use defines a continuum: With discretionary use, the operator has freedom to decide whether or not to use the system, and with mandatory use, the operator is forced to use the system (Rawstorne et al. 1998). The relationships among TAM constructs have been consistently confirmed by studies where users had some discretion in using the system. However, these relationships differ for mandatory use. Although use might seem invariant when it is mandated, its *extent* can vary (Hartwick and Barki 1994). In other words, even under forced use, an individual may choose to delay, obstruct, underutilize, or even sabotage the system (Leonard-Barton 1988).

The original TAM cannot adequately explain technology acceptance in mandatory settings. In one study, attitude toward using a technology did not affect BI, but it did affect PU (Brown et al. 2002). This disconnect between attitudes and BI reflects the fact that employees are forced to, and thus intend to, use the system, regardless of their attitudes. This observation is consistent with Rawstorne et al.'s (1998) argument that the user intention construct is inappropriate in a mandatory adoption environment. In addition, unlike many previous studies where PU was found the primary determinant of acceptance (e.g., Davis 1989; Venkatesh and Davis 2000; Gefen et al. 2003; Karahanna et al. 2006), the PEOU-acceptance link is stronger than the PU-acceptance link in mandatory use environments (Adamson and Shine 2003; Brown et al. 2002).

4 An integrated view of automation acceptance

We integrate the findings of the previous two sections into the Automation Acceptance Model (AAM). This framework combines important automation-related constructs from TAM and the CE literature (Fig. 2). TAM has strong theoretical roots in the Theory of Reasoned Action (Fishbein and Ajzen 1975) and is a well-validated framework in a variety of domains. These properties make TAM an apt framework for modeling automation acceptance.

The basic TAM (from Fig. 1) constitutes the core of the AAM (shaded in gray in Fig. 2), and relevant constructs are added to make the model more specific to automation acceptance. The importance of incorporating the interactive nature of many automated systems is captured via feedback mechanisms that relate prior system use to user beliefs. Some of the external variables that may influence compatibility, trust, PU, and PEOU in AAM are subjective norms, voluntariness, and experience. The external variables in TAM are used by AAM to account for system design, user and task characteristics, and organizational influences (Davis et al. 1989).

Both CE and IS communities have advocated designs that incorporate situation and context (Inagaki 2006; Rogers 1995; Goodhue and Thompson 1995; Karahanna et al. 2006). The job relevance construct in TAM2 operationalizes the need to design automation that addresses the task needs (Venkatesh and Davis 2000). A related factor for acceptance is prior use. IS researchers suggest that greater agreement between an automation and user's past experience will increase the likelihood of adopting the new technology (Dishaw and Strong 1998). The compatibility construct in the AAM captures these ideas. The influence of perceived compatibility on the attitude toward use is mediated by PU and PEOU (Dishaw and Strong 1999; Karahanna et al. 2006). In addition, compatibility directly affects trust as indicated by the solid arrow in Fig. 2.

The importance of trust in automation adoption has been emphasized by CE researchers (e.g., Lee and Moray 1994; Parasuraman et al. 2008). Trust has not received as much attention by the IS community but is considered an important influence in the use of electronic information systems and e-commerce (e.g., Gefen et al. 2003; Carter and Bélanger 2005; Pavlou 2003). The results confirm the influence of trust on automation, both when trust is considered as a direct determinant of BI and as an indirect influence through PU, PEOU, and perceived risk. In AAM, we adopt an approach similar to Pavlou's (2003), hypothesizing that trust influences BI directly and indirectly through PU and PEOU.

An emergent theme from the CE community concerning automation adoption is the issue of agency and the influence of levels of automation. This issue has not been a focus of IS research, possibly because IS research focuses on technology such as computer software and office applications, where agency and mixed-initiative control are uncommon. CE research, on the other hand, has dealt with agent-like automation in areas such as traffic safety, where drivers are less likely to accept automation that restricts

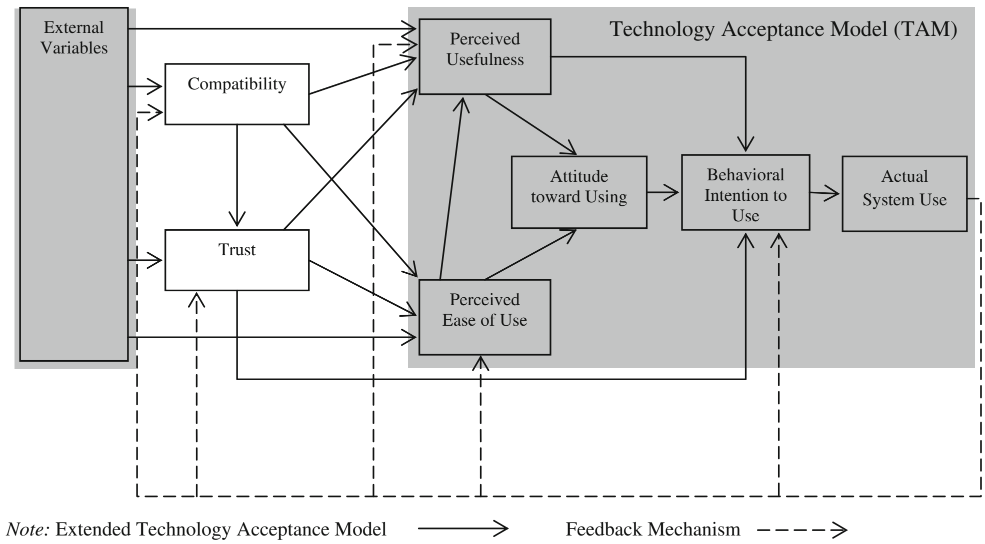

Fig. 2 TAM augmented to create the Automation Acceptance Model (AAM). *Solid arrow* represents Extended Technology Acceptance Model, and *dashed arrow* represents feedback mechanism

their control, unless effective communication is established between the automation and the driver (Hoc 2001; Inagaki et al. 2008). Hence, the level of automation is hypothesized to influence perceptions of situation and context compatibility and is therefore considered in the external variable category.

In mandatory settings, PEOU is a stronger predictor of acceptance compared with PU (Brown et al. 2002; Adamson and Shine 2003). This finding does not suggest the addition of any construct to the model but rather may influence hypotheses made regarding the magnitude of effects. Voluntariness can moderate the influence of subjective norm on BI (Venkatesh and Davis 2000). Hence, subjective norm can be considered in AAM as an external variable that influences BI. The distinction between discretionary and mandatory use of automation will become increasingly important as automation moves from being primarily mandatory in industrial and military applications to consumer products, such as cars, where it is discretionary.

Feedback mechanisms are rarely examined in acceptance models such as TAM. Kim and Malhotra (2005) argue that research has focused on "the influence of user evaluations on user behavior rather than in the opposite direction" (p. 744). In other words, beliefs and perceptions toward a system are examined as determinants of behavior; however, the effect of behavior on future beliefs and perceptions has often been ignored. One of the few studies on the effect of past experience with a system on beliefs found that past use influenced PEOU (Bajaj and Nidumolu 1998). A more comprehensive model evaluated the effect of prior use on PEOU, PU, and BI and found that prior use affected all three variables (Kim and Malhotra 2005). Similar feedback mechanisms were explored using the Extended Decision Field Theory with results indicating that the consequences of past actions influence attitudes and subsequent decisions (Gao and Lee 2006). The feedback mechanisms identified in these studies exemplify the importance of considering the influence of acceptance on system use *and* system use on acceptance. The AAM shows acceptance as a dynamic bidirectional process rather than a static single-directional process. Previous interactions with the system influence the user's perception of the system, which then influences future interactions. The AAM demonstrates this adaptation process (as dashed arrows in Fig. 2), positing that prior system use influences the level of compatibility perceived by the user, trust in automation, PEOU, PU, and BI.

The AAM does not assert that all effects will be influential for all automation applications; rather, it suggests that the relationships in Fig. 2 influence automation acceptance in many situations. The inclusion of external variables enhances the generalizability of the AAM so that it can incorporate the unique attributes of human–automation interaction. Accounting for these variables along with task–technology compatibility, trust in automation, perceived usefulness, and ease of use, as well as the influence of prior system use, makes the AAM a more comprehensive framework for assessing automation acceptance.

5 Discussion

Although performance and preference are often positively correlated (Nielsen and Levy 1994), high levels of performance do not guarantee acceptance and effective human–technology coagency. Users often reject systems that enhance their performance in favor of systems with less pronounced benefits (El Jaafari et al. 2008; Inagaki et al. 2007; Navarro et al. 2010). As such, analyses of preferences and attitudes should be inseparable components of any automation evaluation effort (Andre and Wickens 1995; Bailey 1993).

Research in the CE domain, investigating human–automation relationship on a macro level, has shown that factors such as trust in automation, effectiveness of automation, and automation's level of authority and autonomy influence automation adoption by users. These findings merge to shape two general themes: task–technology compatibility and trust in automation. These factors fit well with the TAM, developed by Davis (1989) in the IS domain, which can serve as the core of a framework to evaluate acceptance and actual system use based on user perceptions, beliefs, and attitudes, such as those found by CE research. Interestingly, trust and compatibility have been examined in relation to technology acceptance using the TAM framework; although, no one study has covered both constructs.

The AAM describes user adoption of automation by incorporating ideas from both the IS and CS communities. It builds upon TAM and exploits the existing knowledge of factors influencing acceptance within the CE literature to create a more comprehensive model of acceptance. On the basis of the TAM literature, PU and PEOU constitute the primary and secondary determinants of attitude toward use, respectively (e.g., Davis 1989). However, this ordering may change in different automation applications and use contexts. For example, research on mandatory use (Adamson and Shine 2003; Brown et al. 2002), as well as studies on ADASs (Chen and Chen 2011; Xu et al. 2010), indicates that PEOU, compared with PU, has a stronger influence on acceptance. In case of ADASs, the strong effect of PEOU might be attributed to the agent-like nature of the system, i.e., automation that can act autonomously and even take control of the driving task. In these situations, being comfortable with working with the technological teammate can influence a driver's willingness to form a cooperative relationship with the system, more so than the perceptions of system usefulness. Such issues of coagency are not pertinent to most IT applications studied by the IS community, e.g., desktop applications and office automation, where PU is typically the primary determinant of BI.

Both the CE and IS communities have identified trust in technology as an important influence on acceptance (e.g., Lee and Moray 1992, 1994; Carter and Bélanger 2005; Gefen et al. 2003; Pavlou 2003). Task–technology compatibility is another important determinant of acceptance identified by both communities (e.g., Dishaw and Strong 1999; Inagaki 2006; Inagaki et al. 2007; Karahanna et al. 2006; Rogers 1995; Venkatesh and Davis 2000; Venkatesh et al. 2003). On the basis of these findings, AAM is centered on the trust and compatibility constructs; however, the model is flexible and can include constructs needed to describe adoption patterns relevant to a wide range of automation types.

An important feature of AAM is its ability to capture the dynamic nature of the adoption process through feedback mechanisms, which is rarely addressed (examples of such articles include Kim and Malhotra 2005; Bajaj and Nidumolu 1998; Gao and Lee 2006). The experience construct has been a part of many TAM-based models; however, the technology acceptance literature has not rigorously assessed adoption over time. Most studies have considered only a cross-sectional analysis of acceptance. The few other studies that have considered adoption over time have conceptualized exposure as the stage that the participant is in (fixed for everyone) rather than the quality of each participant's experience with the system (e.g., Venkatesh and Davis 2000; Venkatesh et al. 2003, 2000). As such, our knowledge of adoption dynamics is limited. AAM highlights this gap and suggests greater attention to the dynamic adoption process by considering the feedback mechanisms that influence perceptions and beliefs.

The feedback mechanisms of the AAM framework can be validated using a multi-wave experiment. Consider a study in which user perceptions of the system are captured through survey questionnaires administered at several points in time: at the initial introduction of automation (T1), after 2 months of usage (T2), and after 6 months of usage (T3). System use can be measured using system logs during the transition periods between two waves (i.e., T1–T2 and T2–T3 time periods). AAM provides a framework for evaluating the effect of user perceptions at T1 on usage during the T1–T2 period and the effect of perceptions at T2 on usage during the T2–T3 period (TAM relationships), as well as the effect of system use during the T1–T2 period on perceptions at T2 and the effect of system use during the T2–T3 period on perceptions at T3 (feedback mechanisms). Such data would support a thorough assessment of the adoption dynamics shown in the AAM framework.

The adoption dynamics implied in TAM depict a unidirectional process where attitudes influence use. Figure 2 describes AAM with the feedback mechanisms but still emphasizes a flow of information from perception of the system to use intentions, and finally, to actual use. However, adoption is a continuous interactive process (Wilkinson 2011). It reflects the mutual influence of perceptions, beliefs, and use, rather than a simple cause-effect relationship in which user attitudes influence automation usage.

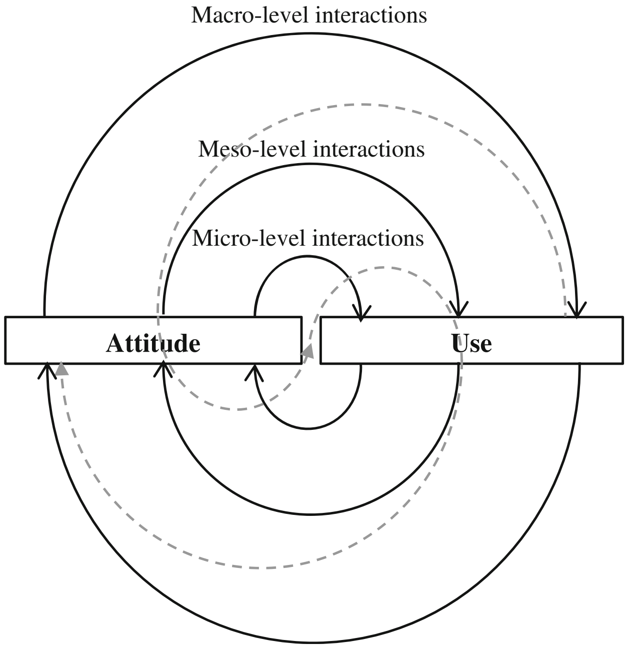

Fig. 3 The dynamic relationship between attitude and use. *Solid arrows* are the intra-level effects, and *dashed arrows* are the inter-level effects

Attitudes influence use, and use influences attitudes. Figure 3 shows the bidirectional multi-level relationship between user's attitudes and use behavior. The attitude–use interactions start at the micro-time scale (e.g., milliseconds to seconds), span to influence at the meso levels (seconds to minutes and minutes to hours) and further to influence at the macro levels (hours to days and days to months), as indicated by nested half-circular arrows. Furthermore, attitude–use influences are not confined to time levels (i.e., intra-level effects, shown by half-circular arrows) but rather can mediate effects at higher as well as lower levels as shown by dashed spiral arrows that represent inter-level effects.

This paper has focused on acceptance by the individual, although the potential role of social factors and social norms on automation acceptance was briefly mentioned. These factors force conformance because deviations from the social norms are often penalized (Bernheim 1994). Understanding the dynamics that underlie social norms and their influence on the perceptions of automation and users' conformance with others' automation acceptance is a critical but unexamined issue. For example, an organizations' priority for traffic safety (i.e., safety climate) as well as its understanding of the benefits of an ADAS shapes the social norms regarding the use of that ADAS within the organization. These norms will, in turn, influence individual drivers' perceptions of the ADAS and ultimately, their use decisions. For an example of how sharing automation reliance information might influence others' reliance, see Gao and Lee (2006).

This article develops AAM to integrate the CE and IS perspectives into automation acceptance and reliance. AAM captures the main determinants of acceptance contributed by the CE and IS communities. The CE community has contributed a major body of evidence describing the trust and task compatibility constructs in the process control, driving, and aviation domains. The IS community has demonstrated the importance of perceived usefulness and perceived ease of use. AAM integrates these findings in a very general framework that can consider a broad array of domain-specific considerations. The value of this framework may be greatest for consumer products, such as ADASs, which are quickly being incorporated into cars. Such systems have features typical of those studied by the IS community (e.g., providing new types and forms of information) and those systems studied by the CE community (e.g., supporting joint control with a high degree of agency). ADAS is one of many examples where sophisticated information and control systems are becoming part of our everyday lives. Because the performance of such joint cognitive systems depends not on technological sophistication but on acceptance and appropriate reliance, pooling findings of the CE and IS communities is needed to guide design and assess performance. AAM provides a first step in integrating these findings and suggesting new research directions. The dynamic, multi-level nature of automation adoption and the bidirectional influences of attitudes and use represent critical and relatively unexamined features of systems that increasingly rely on effective human–technology coagency.

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