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ADOPTION AND USE OF AI TOOLS: A RESEARCH AGENDA GROUNDED IN UTAUT

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Abstract

This paper is motivated by the widespread availability of AI tools, whose adoption and consequent benefits are still a question mark. As a first step, some critical issues that relate to AI tools in general, humans in the context of AI tools, and AI tools in the context of operations management are identified. A discussion of how these issues could hinder employee adoption and use of AI tools is presented. Building on this discussion, the unified theory of acceptance and use of technology (UTAUT) is used as a theoretical basis to propose individual characteristics, technology characteristics, environmental characteristics and interventions as viable research directions that could not only contribute to the adoption literature, particularly as it relates to AI tools, but also, if pursued, such research could help organizations positively influence the adoption of AI tools.

Keywords: AI tools, UTAUT, employee adoption, technology use

1. Introduction

Artificial intelligence (AI) saw its genesis in the mid-1950s. Despite its initial promise, it stuttered to what seemed like an end for a variety of reasons such as technology limitations, including data processing capability, handling different types of data, and approximating human thinking. The tremendous growth of technology has been a critical contributing factor to the resurgence of AI tools that remedy the limitations of the past. The growth of AI tools and its promise of benefits for organizations are unprecedented. Organizations are scrambling to invest in, deploy and leverage AI tools in various areas of organizational functioning to harvest its benefits, create competitive advantage, and enhance performance.

The definition of AI tools and what they entail itself is continuing to evolve, especially with the integration with many new and modern technologies, such as Internet of Things, and data, such as big data (Y. Wang et al. 2019). There is a growing body of research on various aspects of AI tools, especially focused on design of AI tools ranging from requirements elicitation (Z. Wang et al. 2019) to technical aspects (Romanova et al. 2019) in a variety of settings such as supply chain (Priore et al. 2019), biomedicine (Kocheturov et al. 2019), and smart healthcare in clinical settings (Pan et al. 2019). Performance of such AI-based tools, especially in comparison to previous approaches and algorithms, is of interest (Razzaghi et al. 2019), with a particular focus on avoiding biases that can creep into models, especially when learning comes from data that is riddled with bias (Lambrecht and Tucker 2019).

Not unlike numerous technologies before AI that came with extraordinary promise, the ground reality tends to be far different. A major hurdle to garnering benefits is adoption and use of any technology. AI tools are and will continue to be no different. At the organizational level, amongst the problems hindering adoption are several usual suspects—such as the need for infrastructure, the need for appropriate training, the lack of a business case, and inadequate skills to name but a few. Several articles have been written in the trade press that outline these problems.[1] Although there may be unique elements that hinder the organizational adoption of AI tools, I argue that some of the problems are typical of any technology implementation.

Turning to employee adoption of AI tools, which is a necessary step to organizational adoption and garnering of benefits, unlike in the case of organizational adoption, there are a number of unique aspects of AI tools that could play a critical role, especially in hindering employee adoption. Employee adoption of technology is a mature area of research, with many established theories that successfully predict the adoption and use of a broad range of technologies (see Venkatesh et al. 2016). The unified theory of acceptance and use of technology (UTAUT; Venkatesh et al. 2003) is among the most widely used theories that has successfully replicated numerous times and, in fact, used to study a variety of technologies and even contexts beyond employee adoption. Critically, contextual conditions and attributes unique to specific technologies are known to play a role in the ultimate adoption and use of those technologies (for examples, see Brown et al. 2010; Hong et al. 2014). Contextual issues that can influence employee adoption of AI are thus the focus of this work. AI tools, at least currently, as noted earlier, span a wide spectrum to provide decision making support and even decision making in a variety of contexts. The particular shift with AI tools is not only powered by the availability of enormous amount of data, but also by a shift from decision support to actual decision making. With AI tools, the human decision maker—i.e., employee—could thus be relegated to playing a secondary role or have no role to play. On the positive side, AI tools may indeed be able to process a lot of data, even in real-time, to arrive at inferences that can be the basis of good

[1] Two illustrative sources of organizational challenges are: https://petuum.com/2019/04/02/seven-challenges-of-adopting-artificial-intelligence-solutions/ and https://neoteric.eu/blog/12-challenges-of-ai-adoption/

decisions, thus freeing up employees for more strategic and/or abstract thinking. On the flip side, for instance, the widely publicized AI tool used by Amazon that led to biases against women job applicants—a tool that was used in screening applications (see Schuetz and Venkatesh 2020). Undoubtedly, this is but one example of an AI tool replacing a human being in making a decision of substantial significance. Taking the human intervention away from the decision-making process means organizations rely on AI tools to make decisions, the consequences of which may not be felt until later in the business process. Thus, a middle ground would seem that AI tools are used by employees in much the same way as decision support tools were in the past, albeit with a focus on more sophisticated problems and to support more complex decisions. This would give the employee the leeway to leverage the AI tools and its power to support decision making, as he or she should see fit. It is the adoption of AI tools in such a middle ground that is the focus of this paper.

Moving beyond the general topic of AI tools, it is important to consider how the AI tool adoption will be unique in the case of tools built to support operations management (OM). One clear distinguishing feature of OM, compared to other business disciplines except perhaps information systems (IS), is that it necessarily spans across a large chain of business functioning by connecting an organization to upstream activities tied to vendors all the way to downstream activities tied to distribution and even retail. By relating to the entire supply chain and logistics, OM is a broad discipline and tools that seek to support OM may need to factor this. Such OM problems have been long supported by various approaches powered by mathematical models and algorithms, and they are progressively seeing the use if AI, especially machine learning, approaches in the quest for solutions.

Against this backdrop, this paper has the specific objectives:

(1) identify general issues related to AI tools and unique issues related to AI tools in the context of OM that could potentially hinder employee adoption and use of such tools; and

(2) using UTAUT as the underlying theoretical basis, present a research agenda to study the adoption and use of AI tools in OM, with implications for the broader adoption and use of AI tools by employees in organizations.

2. AI Tools and Operations Management: What's General and What's Unique?

As we consider AI tools for OM, it is important to recognize and identify the several issues that AI tools present that may hinder their adoption by employees. These issues are organized into three areas: (1) general issues with AI tools; (2) general challenges with employees; and (3) unique issues with AI tools for OM.

2.1 General Issues with AI Tools

(1) *Model is blackboxed:* With AI tools, often, the underlying model itself is blackboxed and the user has little or no visibility into the underlying algorithm or process that renders the decision. Users are unlikely to always embrace this, especially if there is accountability on the part of the user for the consequences.

(2) *Model errors:* Almost by definition, a model is bound to make mistakes, given that it is, after all, a representation of reality. Such mistakes are particularly more likely in dynamic environments and/or environments where there is greater uncertainly or lack of data, as may sometimes be the case when extra-organization entities are involved, which is often the case in supply-chain and logistics matters. With errors come a lack of trust in the model decisions or recommendations. With mistakes building up over time, there could be a potential negative impact on use over time.

(3) *Model learning takes time:* Related to but somewhat distinct from the issue of model errors is the fact, AI models will learn over time that will likely and hopefully result in the performance improving over time. Such learning and early mistakes will be particularly more pronounced when, as noted in the previous point, the environment is dynamic in contexts like supply-chain and logistics where more partners, limited data and/or data of questionable quality may be involved.

(4) *Model bias:* Models do tend to have biases, some of which may be emergent and unknown initially (see Schuetz and Venkatesh 2020) such as in the case of the Amazon job applicant screening tool. The bigger the biases that develop, especially those with significant adverse consequences, the greater the resistance that is likely to build.

2.2 General Challenges with Employees

(5) *Human biases and greater trust in human judgment:* Employees, each with their unique background and experiences in general and experiences in the specific organization, business unit and/or job, will have numerous biases. Some of these biases would be the result of heuristics that they have developed over time. Although these biases could be as severe or worse than what AI tools may have/develop and such biases could lead to bigger or more frequent mistakes than what AI tools may make, employees may simply have greater trust in their own judgment or judgment of their coworkers.

(6) *Algorithm aversion:* An interesting and evolving issue seems to be a particular characteristic that manifests as an aversion to what the core of AI tools are—i.e., algorithms. This issue is broader than the earlier set of issues identified earlier related to models in that this particular issue has nothing to do with whether the model is right or

wrong, rather it is simply a matter of a preference for no algorithm—i.e., no AI tools—altogether.

2.3 Unique Issues with AI tools for OM

(7) *More stakeholders:* Compared to AI tools built to serve specific business units or jobs within specific business units, AI tools and concomitant algorithms/models for OM will necessarily need to take more stakeholders data/information into account because of the very nature of the supply chain and logistics activities. This will build greater uncertainty and may lead to, as articulated earlier, errors and biases. Beyond that, due to such challenges, employees using AI tools to support OM activities may be reluctant to adopt and use them.

(8) *Incomplete and/or missing data:* Models will often be based on incomplete or missing data, and this is likely to be exacerbated with more stakeholders being involved and especially more extra-organizational stakeholders involved, which, as noted earlier, is likely to be the case in an OM context.

(9) *Unknown or incorrect assumptions:* Going beyond the availability of data is that models, given that they are a representation of reality, are based on numerous assumptions. For models that are narrower in scope, such as the ones that are supporting specific jobs or specific jobs within specific business units with little or no interfaces with other business units or extra-organization entities, such assumptions may be accurate. However, in an OM context, just like missing or incomplete data, assumptions made may be unknown/unspecified or incorrect—such assumptions can in turn be a direct contributor to some of the issues, such as model errors, articulated earlier.

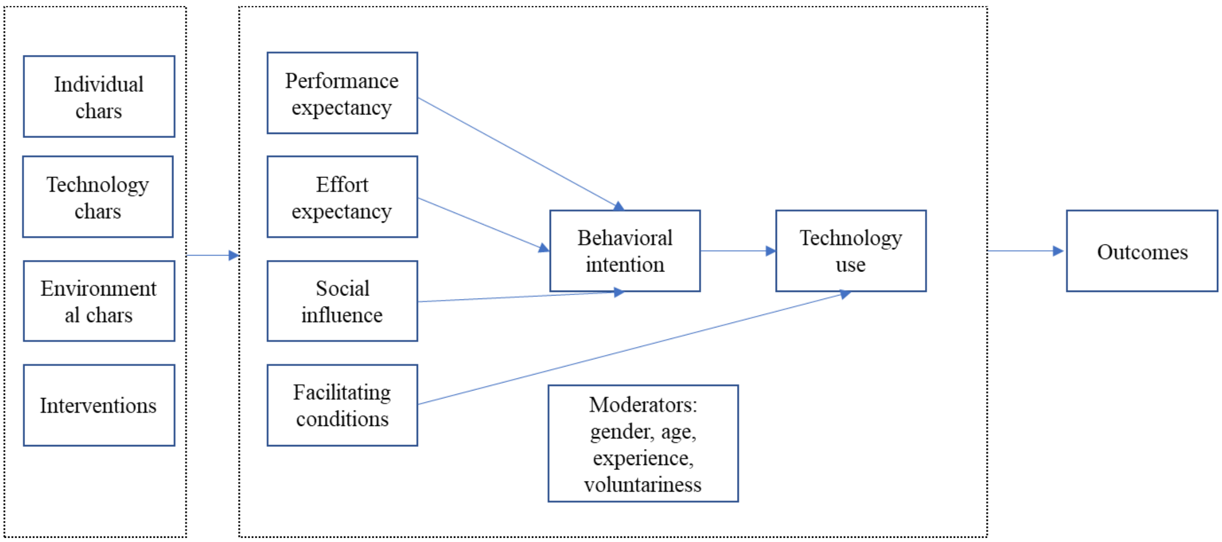
(10) *Changing landscape:* Due to the number of stakeholders involved and the complex and long chain involved, the landscape of parameters, not just assumptions, that influence activities may be changing in ways that are not readily apparent and thus cannot be used to inform the model, especially in a dynamic manner. Much like faulty assumptions or missing data, such a situation is also likely to contribute to problems, such as model errors, like the ones articulated earlier.

In sum, there are several issues with AI tools, some general, some specific to employees, and some unique to AI tools in an OM context that will play a role in potentially hindering employee adoption.

3. Research Agenda

Against the backdrop of the issues discussed earlier, in this section, a research agenda using UTAUT as the underlying theoretical basis is proposed. Note that UTAUT has been used to study the full spectrum of technology adoption from initial adoption to post-adoptive use (e.g., Venkatesh et al. 2011). The key ideas of UTAUT from Venkatesh et al. (2003) are presented here. UTAUT has four predictors of intention to use and technology use: performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs are defined as follows: performance expectancy is defined as the degree to which an individual believes that using a system will enhance their job performance; effort expectancy is defined as the degree of ease associated with the use of the system; social influence refers to an individual's perception that important others believe that he or she should use the new system; and facilitating conditions refers to individual's belief that an organizational and technical infrastructure exists to support use of the system. Up to four variables moderate various relationships: gender, age, experience, and voluntariness of use (for a discussion of moderators, see Morris and Venkatesh 2000; Morris et al. 2005; Venkatesh and Morris 2000; Venkatesh et al. 2004). Fig. 1 presents UTAUT and the future research directions suggested. Table 1 maps the issues related to AI tools with the proposed future research directions including illustrative research questions.

Fig. 1 UTAUT and Proposed Future Research Directions



I have, in the past, proposed research agendas for the topic of individual-level adoption and use of technology both in general (Venkatesh et al. 2007; Venkatesh and Bala 2008; Venkatesh et al. 2016; Zhang and Venkatesh 2018) and in specific contexts including those related to operations management (e.g., Venkatesh 2006, 2013). These serve as the backdrop to propose research that can be conducted to better understand and foster employee adoption and use of AI tools, with a particular eye toward how to increase such adoption and use, especially in the OM context. As with most research agendas, the suggestions here are not meant to be exhaustive but meant to provide illustrations and conceptual ideas that can spur further investigations.

Table 1. Research Agenda

AI Tool Issues	**UTAUT-related Research Directions**	**Illustrations**

1. Model is blackboxed 2. Model errors 3. Model learning takes time 4. Model bias All these issues related to the model create situations of uncertainty that users have to embrace and/or tolerate.	• Individual characteristics • Technology characteristics • Environmental characteristics • Interventions	• Role of personality in influencing UTAUT predictors. Some individual characteristics could be moderators of the impact of model opacity on UTAUT predictors and the impact of UTAUT predictors on outcomes. • Design characteristics (such as transparency) can enhance perceptions about UTAUT predictors (such as performance expectancy). Similarly, some design characteristics could serve as moderators of the impact of the relationship of the perceptions of the model to UTAUT predictors and UTAUT predictors to outcomes. • Some situations lead to higher levels of model opacity and consequent negative impacts on UTAUT predictors and/or moderators, as noted above. • Interventions are always crucial to foster adoption and use—and when faced with new models of decision making and related impacts on job characteristics, interventions will be especially critical. Interventions can be designed such that they vary depending on various other characteristics. For instance, the interventions for the more risk-averse may be different.
5. Human biases and greater trust in human judgment 6. Algorithm aversion These relate to issues employees can have that hinder their willingness to adopt AI tools, especially the more opaque the tools are.	• Individual characteristics • Technology characteristics • Environmental characteristics • Interventions	The ideas here are similar in spirit to what was is outlined above in that various aspects of individuals, the design of the tool, and the environment will play a role. In addition, interventions can be designed to enhance adoption and use.
7. More stakeholders 8. Incomplete and/or missing data	• Individual characteristics • Technology characteristics	Building on the spirit of what has already been noted above, OM contexts create greater levels of uncertainty and incomplete information. The impacts of

9. Unknown or incorrect assumptions 10. Changing landscape	• Environmental characteristics • Interventions	these issues can be especially significant in terms of when, where, how, and who will adopt and use AI tools. For instance, the more the stakeholders who are involved and in a dynamic environment, with a great of missing data, the more likely there could be barriers to adoption, and careful investigation and planning of interventions will be critical.
General	• Outcomes	Critical employee outcomes, such as job characteristics, job satisfaction, job stress and job performance, may be affected by the use of AI tools. Accumulating benefits at the employee level is critical to get higher-level (e.g., business unit, organizational) benefits.

As noted in Venkatesh et al. (2016) and associated works (Venkatesh 2014; Venkatesh et al. 2014), UTAUT has served as a powerful general theoretical model and its embedded constructs have been predictive in a variety of contexts and among a variety of technologies—agile systems (Hong et al. 2011), digital libraries (Hong et al. 2001; Thong et al. 2002), e-government (Chan et al. 2010; Venkatesh et al. 2011; Venkatesh et al. 2012; Venkatesh et al. 2016), e-tax filing (Hu et al. 2009), mobile data services (Hong et al. 2008; Xu et al. 2017), and personal ICT (Thong et al. 2011). Building on the prior general research agendas, there are the following four key research opportunities here: (1) antecedents/determinants of UTAUT constructs including interventions; (2) moderators of UTAUT relationships; (3) new predictors; and (4) consequences.

3.1. Antecedents/Determinants and UTAUT

One of the most fruitful and important avenues leveraging UTAUT as a theoretical basis is to examine antecedents/determinants that are tailored to the particular technology. A general framework adapted from Thong (1999), Venkatesh et al. (2007), Venkatesh and Bala (2008), and Venkatesh et al. (2016) include individual characteristics, such as personality, technology characteristics, such as quality, environmental characteristics (including as perceived by the employee), such as culture of innovation, and interventions, such as training. I elaborate on these next.

Individual characteristics are critical in most technology adoption and use contexts. In this particular case, given the likelihood of errors, uncertainty, and opaqueness, personality characteristics related to these attributes of the technology may be particularly relevant. Individuals who are likely to be more risk-seeking, tolerant of uncertainty, and with a desire to learn are more likely to adopt AI tools. Beyond this, traditional technology-related traits, such as computer self-efficacy and computer playfulness (see Venkatesh 2000; Venkatesh and Davis 1996), could also play a role. General personality traits could also be relevant. These traits can influence the various predictors in UTAUT, especially performance expectancy, effort expectancy and facilitating conditions. Together, these individual characteristics can play a role in how employees deal with issues with the AI tools and/or general challenges faced by employees Overall, researchers should investigate potential traits that could foster or hinder the adoption of AI tools. Using this knowledge, organizations can then identify those who may be able to create a positive environment around the technology.

Technology characteristics can be examined either as perceptions of employees or objective characteristics depending on the nature of the investigation. The particular characteristics of AI tools connected to the various potential challenges, which were described earlier, could play a role. For instance, perceptions of model errors by employees or perceptions of the availability or complete information from other entities in the supply chain could have an impact on UTAUT predictors, especially performance expectancy. If multiple tools were to be compared, objective characteristics of the different competing options on the various parameters, related to the errors, could be examined to see which of them has a strong/substantial effect. Further, design characteristics of AI tools, especially as it relates to the model, such as transparency, could influence UTAUT predictors.

Environmental characteristics including the organizational climate that promotes innovation, learning and other aspects that will allow the tools and associated challenges to work themselves out over a period of time will likely lead employees to adopt and use such tools. Like with technology characteristics, depending on the nature of the studies, i.e., one organization [business unit] being studied or several organizations [business units] being studied, these investigations can also be conducted as perceptions of employees or defined characteristics of specific organizations [business units]. A number of specific attributes pertaining to the environment in which AI tools are used can have an impact on UTAUT predictors. These include the range and number of stakeholders, the lack of data or incomplete or missing data, uncertainty, biases, and extent to which the environment itself is dynamic. All of these environmental characteristics can vary independently or in tandem to create a variety of situations that can play a key role in determining UTAUT predictors.

Interventions, ranging from generic training to various types of training to innovative approaches using gamification (see Venkatesh 1999), could be used to study the impact on adoption and use. Venkatesh and Bala (2008) provide an elaborate framework for studying interventions and their impacts on technology adoption. In particular, when there is likely to be significant uncertainly surrounding the workings of the system, appropriate project management practices may be critical to achieving not only the desired project outcomes, but also the desired employee outcomes (Morris and Venkatesh 2010; Rai et al. 2009; Sykes and Venkatesh 2017; Sykes et al. 2014). Although good project management practices to include significant roles for the users is generally important, it could be expected that they will even more important given the potential problems and uncertainty surrounding supply-chain management systems.

3.2. Moderators

The four categories of constructs, discussed in section 3.1, could potentially play a moderating role as well. To illustrate, it is possible that individual characteristics can moderate the effect of one or more of the UTAUT predictors (e.g., performance expectancy) on intention or use. Similarly, it is possible for environmental variables to play a moderating role. For instance, it is possible that high tolerance for uncertainty could result in a situation where low performance expectancy, say due to high model errors, may not have as detrimental an effect. Another example is where a favorable climate of innovation may result in a stronger effect of social influence on intention. Beyond this, these relationships could vary across cultures (Hoehle et al. 2015; Maruping et al. 2019; Thongpananl et al. 2018; Venkatesh et al. 2010, 2016) and time (Venkatesh et al. 2006). Further, a variety of these effects could be non-linear (Brown et al. 2008, 2012, 2014; Venkatesh and Goyal 2010).

3.3. New Predictors

Going beyond direct effects on UTAUT predictors discussed in section 3.1 and the moderating effects discussed in section 3.2, these variables can potentially have direct effects on intention and use or even downstream outcomes/consequences. It should be noted that beyond the sets of constructs, described in section 3.1, that could influence the various UTAUT predictors or directly influence outcomes, such as intention, use and/or other outcomes, there could be other predictors with direct and/or interaction effects on outcomes. For instance, it is possible to envision that environmental variables will have an effect on intention, use and/or outcomes of using AI tools. The context can often create particular variables that could drive intention and/or use. An important example of adding predictors to UTAUT can be readily seen in the evolution of UTAUT to UTAUT 2 (Venkatesh et al. 2012). UTAUT 2 was created by tailoring UTAUT to the context of consumers using technologies for personal use and specifically adding three predictors (e.g., habit). Additionally, modifications were made to UTAUT in UTAUT 2 by dropping voluntariness of use as a moderator that in turn suggests that, the discussion earlier, could include addition and/or deletion of main effects (predictors) and/or moderators.

3.4. Outcomes/Consequences

The various outcomes/consequences that are typically studied in the technology adoption literature, such as intention, behavioral expectation and use, should be studied (Maruping et al. 2017; Venkatesh et al. 2008). In addition, the impacts of AI tools on job characteristics (Bala and Venkatesh 2013; Morris and Venkatesh 2010) merit attention. Various employee outcomes, ranging from job performance and job satisfaction to job stress should be studied (Sykes 2015; Sykes and Venkatesh 2017).

4. Conclusion

This paper presented a research agenda to study the employee adoption and use of AI tools. UTAUT, which is one of the most widely used theories to explain individual-level adoption and use, is used as a theoretical basis for the proposed agenda. Based on ten issues with AI tools (e.g., model bias), including issues specific to AI tools in operations management (e.g., incomplete information from extra-organizational stakeholders), individual characteristics (e.g., tolerance for uncertainty), technology characteristics (e.g., model quality), environmental characteristics (e.g., innovation climate), and interventions (e.g., gamified training) are proposed as possible determinants of UTAUT constructs, moderators of UTAUT relationships, and possible additional direct predictors of employee adoption and use.

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