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# Is Artificial Intelligence Attractive? An Empirical Study on User’s Intention to Use AI-Enabled Applications

Zhao Gary Yu

Omar El-Gayar

Tu Cindy Zhiling

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Gary Yu Zhao
Dakota State University
gary.zhao@trojans.dsu.edu

Omar El-Gayar
Dakota State University
omar.el-gayar@dsu.edu

Cindy Zhiling Tu
Northwest Missouri State University
cindytu@nwmissouri.edu

## Abstract

*Artificial Intelligence (AI) technologies such as machine learning (ML), natural language processing (NLP), and image recognition, are being incorporated into a wide variety of applications. These AI-enabled applications (AIapps) promise to reshape people's lives. However, despite the proliferation of AI-related research, very little research has focused on how AIapps' unique characteristics affect an individual's adoption behavior. This study examines factors influencing an individual's intention to use AIapps with a proposed research model based on the Task-Technology Fit (TTF) as the underlying theoretical framework. The research model is empirically evaluated using the survey data and SEM method. Theoretically, this study focuses on how the unique characteristics of AIapps influence the task-technology fit and drive the intention of use. The findings are expected to help AIapp developers to evaluate the relative importance of AIapp features which can provide insights into the technology characteristics and identify priorities for further research and development.*

**Keywords:** AI-enabled application, AI features, Task-technology fit, intention to use.

## 1. Introduction

Generally, artificial intelligence (AI) refers to the information technology (IT) capabilities that can perform tasks that possibly require intelligence (Russell & Norvig, 2010). Nowadays, AI technologies, including machine learning (ML), natural language processing (NLP), pattern recognition, and virtual agents, are being embedded in existing information systems and new applications. The dramatic growth of big data, computing power, and intelligence algorithm has significantly driven the development of AI-enabled applications (AIapps). As an emerging technology, AIapps refers to the applications that incorporate AI technologies and have their own unique capabilities such as machine learning, human-like interaction, knowledge representation and reasoning, and relative autonomy. Such capabilities help users complete their tasks effectively and efficiently. Further, AIapps combined with personal devices such as smartphones, tablets, laptops, and IoTs, provide users with utmost accessibility and pervasiveness.

According to Gartner, Inc., worldwide AI applications revenue is forecast to total $62.5 billion in 2022, an increase of 21.3% from 2021 (*Gartner Forecasts Worldwide Artificial Intelligence Software Market to Reach $62 Billion in 2022*, 2021). However, even considering that availability and accessibility of AIapps, people may not use them regularly. A recent survey showed that while 98% of iPhone users had used Siri, only 30% used it regularly and 70% rarely or only occasionally used it (Cowan et al., 2017). How attractive is AI to individual users? Why do people opt to use AIapps?

The users are free to use AIapps to assist themselves in their daily lives. Adoption and use of AIapps are entirely voluntary. Contemporary researchers have evaluated various factors that influence users' adoption of AIapps based on different theoretical frameworks. Existing studies examined the primary positive factors such as usefulness, life efficiency, ease of use, facilitating, social norm and conformity, perceived enjoyment, self-efficacy, trust, etc. The negative factors included perceived risk, algorithm nontransparent, outcome variance, etc. Few studies examined the factor of task-technology fit that influences adoption of specific AIapps, e.g., an AI-enabled smart library app (Liu et al., 2021) and an AI-enabled human resource app (Pillai & Sivathanu, 2020b). Moreover, existing research on the acceptance of AIapps emphasized specific AIapp such as Siri (Kaplan & Haenlein, 2019), Google Assistant (Choi & Drumwright, 2021), Alexa (McLean et al., 2021), Tourism Chatbot (Pillai & Sivathanu, 2020a), AI voice assistant (Malodia et al., 2022), AI banking app (Lee & Chen, 2022). Further, many past research tended to focus on the adoption of AIapps in the organizational level, e.g., Pillai & Sivathanu, (2020b) examined the acceptance of an AI-enabled talent acquisition system for the human resource department, Fernandes & Oliveira, (2021) discussed the adoption of the voice assistant in the company's customer service, while Fu et al., (2020) examined the adoption of an AI-enabled grading application in the education institutions. Overall, theoretically, current AIapps adoption research relied predominantly on TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) models as the underlying theoretical models. There is the lack of empirical analysis that focuses on the unique characteristics of AIapp itself and its role in influencing individual users' adoption.

Accordingly, this study aims to investigate unique characteristics of AIapps affecting individual's intention to use AIapps with a theoretical framework based on the Task-technology Fit (TTF) model. This study also enriches the general Task-Technology Fit model (TTF) by investigating how unique AI features may affect and mediate users' acceptance intention and behavior. The research results will help AIapp developers or vendors better understand individual users' behavior regarding using their applications.

## 2. Background and related work

### 2.1. AI-enabled applications

An AIapp via emotion-sensing facial recognition can detect whether a person is upset, sad, annoyed, or happy and is used to improving customer satisfaction (Haenlein & Kaplan, 2021). AIapps with voice queries and NLP like Amazon Alexa (on Amazon Echo), Siri (iPhone, iPad, iOS laptop), Google Assistant (Google phone, Google Home, Hyundai car), Cortana (Microsoft phone, Windows platform) can help people make calls, send messages, answer questions, provide recommendations, set the alarm, make a to-do list, play music and provide real-time information on weather, traffic, news, sports and more. ELSA Speak with AI functionality can help people learn to speak English. Socratic can assist students with their homework just by submitting a picture of the tasks. Some AIapps run in the background, e.g., online recommendation apps that provide users a playlist for video and music services, e.g., Netflix, YouTube, and Spotify (Cabrera-Sánchez et al., 2021).

AIapps have their unique characteristics that affect users' acceptance. We synthesize and summarize four characteristics from the literature. First, machine learning capability. Machine learning (ML) ability is one of the most distinguishing features of AIapps (Grewal et al., 2021, Martínez-Plumed et al., 2021, Canhoto & Clear, 2020, Alter, 2021, Kushwaha et al., 2021). AIapps must have the ability to continuously learn through data and experience to adapt to their environment (Berente et al., 2021). Ruiz-Real et al., (2021) argue that AI-enabled systems with ML ability have a common application in the big data analyzing field, such as a complicated recommender system based on an enormous volume of inputs.

Second, human-like interacting capability. AIapps must have the ability to interact with people in a natural way (Alter, 2021, Pillai & Sivathanu, 2020b). Recent developed Natural Language Processing and Understanding (NLP/NLU) has already been deployed to a vast majority of daily applications such as customer service chatbots, Siri, Google Assistant, Amazon Alexa, etc. These AIapps can interact with the user as a human (Cabrera-Sánchez et al., 2021, Hasan et al., 2021, Choi & Drumwright, 2021, Martínez-Plumed et al., 2021). A human-like chatbot with an anthropomorphic quality should be able to respond to the user based on the keywords, determine what type of problem is faced by the customer, understand the user's attitude and emotion, predict the feedback of the user, and try to pacify a frustrated user (Canhoto & Clear, 2020, McLean et al., 2021, Sheehan et al., 2020, Fernandes & Oliveira, 2021). Also, a human-like voice AI assistant can be perceived as a friend, and this relationship between the user and an AI assistant brings a sense of social presence to mind, following building a rapport with the AI agent (Choi & Drumwright, 2021, McLean et al., 2021).

Third, knowledge representation and reasoning capability. Reasoning is always associated with human intelligence. Previous efforts in AI were focused on creating an application that could reason by itself, making conclusions from some premises (Martínez-Plumed et al., 2021). Many AIapps such as digital assistants or chatbots are knowledge-based applications that can search, extract, analyze, and represent the knowledge (Ruiz-Real et al., 2021, Grewal et al., 2021, Grundner & Neuhofer, 2021). An AIapp must be able to retrieve, store, transform, process the data from both new and existing sources and represent that into the system using effective models and schemas (Canhoto & Clear, 2020, Puntoni et al., 2021). Moreover, an AIapp should have abilities to draw inferences from provided knowledge (Alter, 2021, Pillai & Sivathanu, 2020b).

Fourth, Autonomy. Contemporary forms of AIapps keep increasing their ability to act independently without human intervention (Liu et al., 2021, Berente et al., 2021, Martínez-Plumed et al., 2021). AIapps eliminate the human emotional component and the flexibility of thought and actions by not following strict rules. This autonomy attribute of AIapps allows them to exceed human capabilities in processing difficult problems (Ruiz-Real et al., 2021).

## 2.2. Adoption of AI-enabled applications

Research examining users' acceptance of an AI-enabled application relied predominantly on TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) models. For example, Cabrera-Sánchez et al. (2021) discussed adoption factors with an extended UTAUT model, while Pillai & Sivathanu (2020a), Fernandes & Oliveira (2021), Kasilingam, (2020), Rese et al., (2020), and Wang et al., (2020) examined the adoption of AI-enabled chatbots for customer service in different contexts based on the TAM model. However, TAM and UTAUT only focus on users' beliefs and attitudes before or after adopting the new technology (Wu & Chen, 2017). Compared with models predicting adoption, the task-technology fit (TTF) (Goodhue & Thompson, 1995) model explains the acceptance of IS due to its characteristics and the fit to the task. Task-technology fit is the degree to which technology helps a user complete their tasks. According to Goodhue & Thompson (1995), users intend to use IS because they believe that they can improve their work performance by using the system if the functions of the technology correspond with their tasks. TAM and UTAUT are not explicitly concerned with the fit between the task and the technology. Furthermore, there are several papers on the adoption of specific AI applications in various contextual settings, such as Google Assistant (Choi & Drumwright, 2021), Siri (Cowan et al., 2017, Hasan et al., 2021), voice assistants in service encounters (Fernandes & Oliveira, 2021), AI chatbots in customer services (Kasilingam, 2020, Kushwaha et al., 2021, Rese et al., 2020, Sheehan et al., 2020, Pillai & Sivathanu, 2020a). None of them accentuates on how unique characteristics of AIapps affect users' use intention. This study synthesizes and generalizes unique characteristics of AIapps from literature and proposes a research model to examine the factors that influence an individual's intention to use AIapps by focusing on the fit of task technology.

# 3. Theoretical Framework

AIapps, like every Information System (IS), can be understood from two perspectives: first, it represents a socio-technical system that relies on the interactions of three key elements: the individual user, the tasks, and the technology; second, it is an application class that can be characterized by its inputs, outputs, and processing capabilities (Goodhue & Thompson, 1995). The Task-Technology Fit (TTF) model emphasizes the fit between technologies and tasks and explains how the fit impacts individual performance (Goodhue & Thompson, 1995). In IS research, TTF has been extended with the Technology Acceptance Model (TAM) leading to an extended TTF model with embedded factors of TAM (Dishaw & Strong, 1999, Mathieson & Keil, 1998, Pagani, 2006, Klopping & McKinney, 2004, El-Gayar et al., 2010). In the extended TTF model, alignment between the capabilities of technology and the requirements of tasks can improve IT utilization. Empirical studies have employed TTF to assess user acceptance in different contexts such as software maintenance tools (Dishaw & Strong, 1999), mobile locatable information systems (Junglas et al., 2008), electronic health record systems (El-Gayar et al., 2010), mobile learning (Bere, 2018), smart library (Liu et al., 2021), talent acquisition systems (Pillai & Sivathanu, 2020b), and blockchain technology (Liang et al., 2021).

AIapps are information systems with a high level of interactivity and intelligence to help users perform tasks (Maedche et al., 2019). Users are more likely to use a technology if they perceive a better fit between the technology and the task (Goodhue & Thompson, 1995, Liu et al., 2021, Pillai & Sivathanu, 2020b). Based on this view, TTF provides a theoretical basis for understanding an individual's acceptance of AIapps, focusing on AIapps characteristics and fit to the tasks.

# 4. Research Model

Based on TTF model, we develop the research model (Figure 1), focusing on the unique features of AIapps such as ML capability, human-like interacting capability, knowledge representing and reasoning capability, autonomy, to examine the influencing factors of user' intention to use AIapps.

Tasks are the activities performed by individuals which convert the inputs into outputs (Goodhue & Thompson, 1995). The characteristics of tasks affect task-technology fit. There are two main task characteristics related to AIapps context. The first is task simplicity. Simple tasks, such as making a phone call, creating a to-do list, and playing music, could be processed very well by the AIapps, with only a little instruction from a person (Maedche et al., 2019, McLean et al., 2021). However, for more complex tasks or decisions, people take over the primary task performance and AIapps is only a helper. The second is task routineness. Goodhue and Thompson (1995) argue that people do not have much analyzable search behavior when doing routine tasks. Generally, the more routine tasks are, the more such tasks can be automated using AIapps (Sturm & Peters, 2020). AIapps commonly work with a predefined set of rules or algorithms to complete repetitive and routine tasks (Davenport & Kirby, 2016). We thus hypothesize:

**H1**: The characteristics of tasks have a positive effect on TTF.

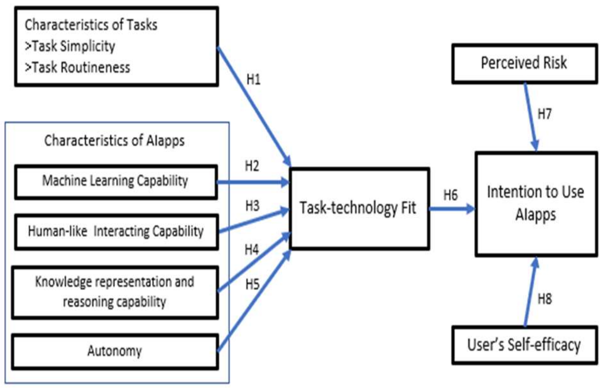


**Figure 1. Research model**

AIapps' characteristics refer to the functional features that are different from other IS technologies. Based on the literature, there are four primary features of AIapps. First is machine learning (ML) capability, which allows AIapp to help users with their tasks by continuously learning new knowledge and adapting to the new environment (Berente et al., 2021, Maedche et al., 2019). This suggests the following hypothesis:

**H2**: The feature of machine learning capability has a positive effect on TTF.

The second is human-like interacting capability. AIapps with human-like interacting capability allows users to communicate with the machine using natural languages in voice or typing as well as body gestures, which reduces the effort of learning and using the application to complete tasks (Choi & Drumwright, 2021, Canhoto & Clear, 2020). This suggests that:

**H3**: The feature of human-like interacting capability has a positive effect on TTF.

Third, knowledge representation and reasoning capability. The ability of knowledge representation and reasoning allows AIapp to provide users high-quality information such as data summary, analysis, and prediction, which brings high-level effectiveness and efficiency to people's tasks (Gursoy et al., 2019, Kasilingam, 2020). We then hypothesize:

**H4**: The feature of knowledge representation and reasoning capability has a positive effect on TTF.

Fourth, Autonomy. Current AIapps run without human intervention or even without people's perceptions (Berente et al., 2021, Maedche et al., 2019). This autonomy feature allows users to use the application easily and complete their tasks efficiently, suggesting the hypothesis:

**H5**: The feature of autonomy has a positive effect on TTF.

The Task-Technology Fit (TTF) reflects the extension to which AIapps meet the task needs of users. Liu et al. (2021) proposed that TTF had a positive effect on the users' acceptance of smart library applications. Pillai & Sivathanu (2020b) found that TTF affected the adoption of AI-based talent acquisition software positively. In this study, it is clear that the more AIapps help users complete their tasks, the more willing users are to use them. Thus, we hypothesize the following:

**H6**: TTF positively influences users' intention to use AIapps.

While AIapps bring people many benefits, they also bring people risks. The concept of perceived risk is a group of several risk components: financial, performance, psychological, social, and physical risk (Kasilingam, 2020). In the information system adoption context, as physical risk is not applicable, it is normally excluded from perceived risk, whereas privacy risk is introduced as it primarily affects online users. Psychological and social risk has been categorized into social risk. Financial risk can be an aftereffect of privacy risk when AI-enabled banking app users' accounts are hacked. Performance risk is a loss in performance due to the failure of a product or service. Social risk is the perception of others when users adopt products or services. AIapp users could be disclosed to all the aforementioned risks. Reflecting on the AIapp adoption context, user perceived risks include users' lack of trust over algorithmic non-transparency, online vulnerabilities, immature technology, bias and uniqueness neglect, social classification, delegation, the privacy of their interactivities, and the potential for private information to be uncovered by third parties (McLean et al., 2021, Grewal et al., 2021, Rese et al., 2020). Perceived risk has been commonly used as one of the extensions of the TAM and UTAUT. This research includes it as one of the variables in our model. Hence, we hypothesize:

**H7**: Perceived risks negatively influence users' intention to use AIapps.

The self-efficacy in using AIapps refers to the users' ability to control the environment to complete the tasks and achieve a particular goal when they use AIapps. Self-efficacy includes individuals' knowledge, understanding, mastery, and use experience of AIapps (Liu et al., 2021). People usually intend to use a new AIapp if they feel comfortable controlling the required resources such as time, money, and personal capabilities. Self-efficacy is an important factor that positively affects users' intention to use AIapps (Pillai & Sivathanu, 2020b). We therefore hypothesize that:

**H8**: Users' self-efficacy positively influences users' intention to use AIapps.

## 5. Methodology

This empirical study aims to understand users' intention to use AIapps and examine the influencing

**Table 2. Variable items and reliability/convergence validity test results**

| Variables | Items | Loading | Cron. α | AVE | CR |
|---|---|---|---|---|---|
| Task Characteristics (TC) >Task Simplicity >Task Routineness | TR1: I need to search the resources, layout and use status information of the applications accurately | 0.704 | 0.791 | 0.503 | 0.848 |
| | TR2: The problems I deal with frequently have been described clearly | 0.71 | | | |
| | TR3: The problems I deal with frequently involve more than one business function | 0.736 | | | |
| | TS1: I frequently deal with the tasks with pre-defined steps | 0.706 | | | |
| | TS2: I frequently deal with ad-hoc, routineness business problems | 0.645 | | | |
| | TS3: The tasks I work on involve answering questions that have been asked in quite that from before | 0.663 | | | |
| Machine Learning Capability (MC) | MC1: I feel this app can learn from previous information | 0.838 | 0.753 | 0.667 | 0.857 |
| | MC2: I feel it can perceive and react to the environment | 0.798 | | | |
| | MC3: I feel this app can act on different scenarios and improve itself | 0.814 | | | |
| Human-like Interacting Capability (HL) | HL1: I like the avatar of this application | 0.802 | 0.758 | 0.583 | 0.847 |
| | HL2: I could choose the avatar's gender in this application | 0.636 | | | |
| | HL3: I like the anthropomorphic voice output in this application | 0.843 | | | |
| | HL4: I feel the application is communicative as human counterparts | 0.757 | | | |
| Knowledge Representing and Reasoning Capability (KC) | KC1: I feel this application is knowledgeable | 0.852 | 0.814 | 0.728 | 0.889 |
| | KC2: I feel that its action is reasonable | 0.87 | | | |
| | KC3: I feel this application can provide understandable advice tailored to me | 0.838 | | | |
| Autonomy (AT) | AT1: I feel this application can do things by itself | 0.867 | 0.803 | 0.718 | 0.884 |
| | AT2: This application takes the initiative | 0.869 | | | |
| | AT3: I feel like this application acts autonomously | 0.803 | | | |
| Perceived Risk (PR) | PR1: I feel the application provider could not secure my privacy | 0.716 | 0.846 | 0.747 | 0.897 |
| | PR2: I feel my personal information could be used by the application provider without my knowledge | 0.924 | | | |
| | PR3: I feel the application provider could leak out my personal data | 0.936 | | | |
| User's self-efficacy (SE) | SE1: I can use this app if I had seen someone else using it before trying it myself | 0.82 | 0.747 | 0.662 | 0.854 |
| | SE2: I can use it if I have the built-in help facility | 0.784 | | | |
| | SE3: I can use it if someone show me how to do it first | 0.836 | | | |
| Task-Technology Fit (TTF) | TTF1: The functions in using this application are appropriate | 0.799 | 0.843 | 0.614 | 0.888 |
| | TTF2: The functions in using AIapps are enough for my tasks | 0.778 | | | |
| | TTF3: I feel the information provided by the application is up-to-date enough for my purposes | 0.762 | | | |
| | TTF4: I feel the information provided by the application is sufficiently authentic | 0.801 | | | |
| | TTF5: I feel the application presents information in a way I understand | 0.779 | | | |
| Intention to Use (UI) | UI1: I intend to use it soon | 0.866 | 0.843 | 0.761 | 0.905 |
| | UI2: I always try to use this application in as many cases/occasions as possible | 0.891 | | | |
| | UI3: I plan to increase my use AIapps in the future | 0.86 | | | |

factors. To test the research model, we use the questionnaire survey and Partial Least Squares Structural Equation Modelling (PLS-SEM) method. The questionnaire includes two parts: demographic characteristics and the measurement items of each variable. All the measurements are developed based on their theoretical meaning and relevant literature. Wherever possible, initial scale items were taken from validated measures in the existing literature, reworded to relate to the context of AIapps' user experience (Table 2). In all cases, the items were scored on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). These items were performed through survey questions. There are 8 independent variables in the research model. The minimum sample size requirements necessary to detect minimum $R^2$ values of 0.10 and 0.25 for a significance level of 10% and to achieve a statistical power of 80% for the designated model complexity are 118 and 45, respectively (Hair et al., 2017). Also, the 10-times rule method for determining the minimum sample size for PLS-SEM (Hair et al., 2017) implies a minimum sample of 80. The target participants of this study were those general users with popular AIapps installed on their devices, e.g., Siri, Google Assistant, Cortana, Alex, etc. We distributed the questionnaire through an online platform named Survey Monkey and followed the two-step approach to analyze the collected data using SmartPLS-3.3.9. First, we examined the fitness and the construct validity of the measurement model by assessing reliability and validity. Second, we examined the structural model to check the strength and direction of the paths among the constructs.

# 6. Results

We collected a total of 479 valid samples. The demographic characteristics of the participants are summarized in Table 1.

**Table 1. Sample characteristics.**

| Characteristics | *N*=479 |
|---|---|
| *Gender* | |
| Male | 53% |
| Female | 47% |
| *Age* | |
| 18-24 years old | 22% |
| 25-34 years old | 26% |
| 35-44 years old | 14% |
| 45-54 years old | 17% |
| 55-65 years old | 10% |
| Over 65 years old | 11% |
| *Education* | |
| High School or under | 18% |
| Bachelor's degree | 41% |
| Master's degree | 35% |
| Doctoral degree | 4% |
| *AIapps Installed on* | |
| iPhone/iPad | 58% |
| Android phone/Tablet | 32% |
| Windows Desktop/Laptop | 4% |
| MacOS Desktop/Laptop | 1% |
| Other devices | 5% |

## 6.1. Measurement model

In this study, the internal consistency coefficient (Cronbach's α coefficient) was measured to test the reliability of the questionnaire. All coefficients ranged from 0.747 to 0.846 (Table 2), i.e., greater than 0.7, indicating that the reliability test of the questionnaire was acceptable.

We conducted confirmatory factor analysis (CFA) to examine the validity, which includes convergent validity and discriminate validity. As shown in Table 2, the average variance extracted (AVE) ranged from 0.503 to 0.761, and composite reliability (CR) ranged from 0.848 to 0.905. All constructs met the acceptable standard (CR>0.7 and AVE>0.5). Additionally, the standard factor loadings ranged from 0.645 to 0.936 (greater than 0.5). These results implied that a high convergent validity of the data existed. The discriminant validity verifies whether the correlation between different factors is small enough as possible. As shown in Table 3, estimated pairwise correlations between factors (i) did not exceed 0.7 and were significantly less than one; and (ii) the square root of AVE for each construct was higher than the correlations coefficient with other factors, which indicated that the scales had good discriminate validity.

The degree of multicollinearity among model constructs was also examined. Values of the variance inflation factor (VIF) varied from 1.228 to 2.512, below the cut-off threshold of 5 (Hair et al., 2017), thereby suggesting that factors were not highly correlated to one another. To reduce potential common method variance, we used existing scales and ensured respondents' anonymity.

## 6.2. Structural model

The significance and magnitude of each hypothesized path and the explanatory power of the overall model were tested by using SmartPLS as depicted in figure 2. Seven paths were significant with a p-value less than 0.05, while one path was not significant. Regarding direct effects (i.e., without controlling for mediating effects), we found a significant and positive relationship between "Task Characteristics" and "Task-Technology Fit" (β = 0.089; p-value = 0.010), thus supporting H1. We also found support for H2, H3, H4, H6, and H8 with a significant, positive relationship between "Task-Technology Fit" and "Machine Learning Capability" (β =0.116; p-value =0.007), "Task-Technology Fit" and "Human-like Interacting Capability" (β =0.256; p-value =0.000), "Task-Technology Fit" and "Knowledge Representing and Reasoning Capability" (β = 0.497; p-value =0.000), "Task-Technology Fit" and "Intention to Use" (β =

**Table 3. Correlation coefficient between latent variables and square root of AVE**

| | AT | HL | UI | KC | MC | PR | TTF | TC | SE |
|---|---|---|---|---|---|---|---|---|---|
| AT | 0.847 | | | | | | | | |
| HL | 0.477 | 0.763 | | | | | | | |
| UI | 0.43 | 0.586 | 0.872 | | | | | | |
| KC | 0.526 | 0.609 | 0.513 | 0.853 | | | | | |
| MC | 0.506 | 0.534 | 0.504 | 0.604 | 0.817 | | | | |
| PR | -0.005 | -0.018 | -0.132 | -0.086 | 0.11 | 0.864 | | | |
| TTF | 0.485 | 0.664 | 0.536 | 0.768 | 0.599 | -0.06 | 0.784 | | |
| TC | 0.443 | 0.476 | 0.534 | 0.491 | 0.504 | 0.077 | 0.514 | 0.709 | |
| SE | 0.55 | 0.584 | 0.458 | 0.621 | 0.442 | -0.082 | 0.614 | 0.46 | 0.814 |

Note: The value on the diagonal in the matrix is the square root of AVE, the remaining figures represent the correlations ($p<0.01$).

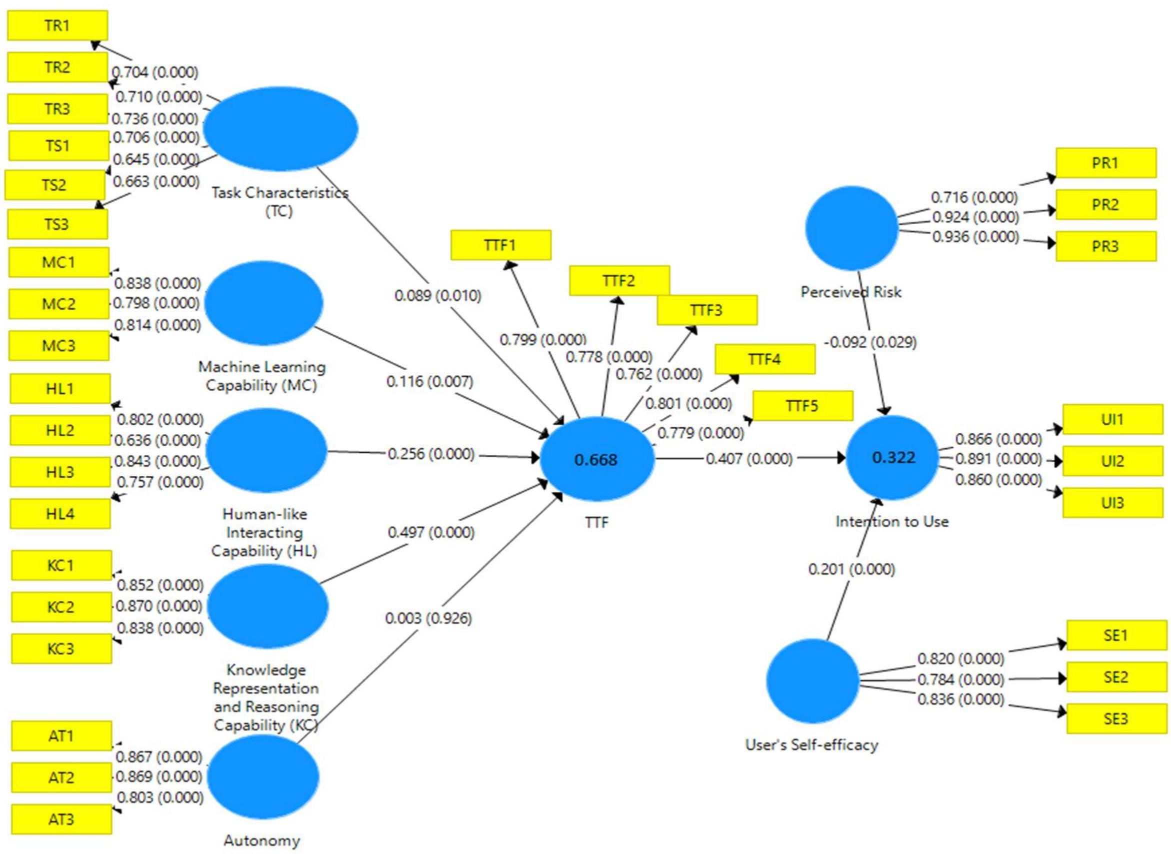


**Figure 2. Hypothesis test results with path coefficients and p-values, Outer loadings and p-values**

0.407; p-value =0.000), "User's Self-efficacy" and "Intention to Use" ($\beta$ = 0.201; p-value =0.000). Further, we found support for H7 with a significant, negative relationship between "Perceived Risk" and "Intention to Use" ($\beta$ = -0.092; p-value =0.029). However, we were unable to verify the expected positive impact of "Perceived Autonomy" (H5: $\beta$ = 0.003; p-value =0.926) on "Task-Technology Fit". The model explained 67 percent ($R^2$=0.67) of variance in TTF; 32 percent ($R^2$=0.32, greater than 30%) of the variance in the intention to use AIapps, which meant that the model had a moderate explanatory power.

## 7. Discussion

In the Task-technology Fit model, task characteristics and technology characteristics affect the fit. Based on the above analysis results, task characteristics, machine learning capability, human-like interacting capability, and knowledge representation and reasoning capability positively affect TTF. Task characteristics include task simplicity and routineness. The simpler and the more routine the task is, the better fit the AIapps can deal with. Davenport & Kirby (2016) classified AI into four intelligence levels: support for human, repetitive task automation, context awareness and learning, and self-awareness. They assert that most contemporary AI applications are in the second level, which typically relies on a fixed set of rules and algorithms. This finding empirically confirms Davenport & Kirby (2016)'s propositions. In all technology characteristics of AIapps, machine learning capability is the most common feature. Higher level of machine learning capability provides a better fit of AIapps for assisting people on various tasks. Prior work employed the concept of adaptability instead of machine learning ability to discuss the influence of AI on tasks (Liu et al., 2021) and the relative advantages (Rijsdijk & Hultink, 2007). The results extend prior work by demonstrating that machine learning capability of AIapps positively affects the task-technology fit. Moreover, AIapps can interact with people in a manner similar to human, e.g., expressing emotions, using natural languages, understanding users' attitudes, etc. The higher level of human-like interacting capability means AIapps can better meet the different task needs. Most AIapps are knowledge-based applications, which can acquire knowledge by searching, extracting, reasoning, and analyzing the data, then representing the knowledge. A stronger knowledge representation and reasoning ability can help users timely and accurately perform tasks, leading to higher TTF (Pillai & Sivathanu, 2020b). This characteristic of AIapps has the highest significance of the impact on the task-technology fit in our tested model.

The results show that TTF positively affects intention to use significantly. The higher TTF means that AIapps can bring users rich and relevant functionalities and fulfill users' needs; thus, driving users' adoption. Moreover, this study indicates that users' self-efficacy positively affects the intention to use AIapps. When users are confident in controlling the required resources and their technical capabilities, they can use new technologies to complete the tasks, thus obtaining higher perceptual matching (i.e., TTF) and better experience (Compeau et al., 1999). Our tested model has an approximate equivalent impact on the use intention between users' self-efficacy and TTF. Further, this study shows the significant negative effect of perceived risk on the use intention. The biggest concern is that individual users do not trust the vendors who can possibly leak their private information to third parties (Chen & Huang, 2017). The tested model shows that AIapps' autonomy characteristic affects TTF positively, but not significantly. This may be due to the users' difficulty in understanding the potential of the technology in automating tasks. Further, the measurements of the autonomy construct may not reflect the relationships accurately between the fit and itself, suggesting the importance of further research. It is also worth noting that the coefficients (β) of these four dimensions are 0.497 for Knowledge Representing and Reasoning Capability, 0.256 for Human-like Interacting Capability, and 0.116 Machine Learning Capability, emphasizing the importance of focusing on knowledge representation and reasoning capabilities of AI-enabled apps.

## 8. Conclusion

This study examined factors influencing an individual's intention to use AIapps using a research model based on the Task-Technology Fit (TTF) as the underlying theoretical framework. The results support the importance of TTF in driving the adoption of AIapps and highlight the importance of specific technology characteristics in driving TTF. These characteristics are Knowledge Representation and Reasoning Capability, Human-like interacting Capability, and Machine Learning Capability. User's self-efficacy positively affects the intention of use while perceived risk negatively influences use intentions.

Overall, this study addresses the AIapps acceptance from an individual perspective. Theoretically, this study improves the understanding of the unique characteristics of AIapps influencing task-technology fit and driving intention of use. Further, we investigated the relative importance of unique AI features that contribute to user acceptance of AIapps, which extends the TTF model to a new context with validated constructs. Practically, such understanding can help AI-enabled application developers better understand individual users' behavior regarding using their applications. Most notably is the ability to evaluate the relative importance of AIapp features which can provide insights into the technical characteristics and identify priorities for further research and development.

Several limitations in the present study may be addressed in future studies. The data obtained was mainly from the U.S. Hence, future research may explore generalizing these results to different countries and cultures. This study collects subjective data using Likert scales. Future extensions may explore complementing subjective data with objective measures such as the length of time users spent on AIapps and how frequently they used these apps throughout the day. Further, over time, users' intention to use new technology can change as they accumulate knowledge and experience. Future research could adopt a longitudinal approach to assess changes over time.

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