Organizational Psychology, 2025, Vol. 15, No. 1, P. 86–103.
DOI: 10.17323/2312-5942-2025-15-1-86-103

ORGANIZATIONAL PSYCHOLOGY

www.orgpsyjournal.hse.ru

Expanding the technology acceptance model: Trust as a mediator in the relationship between environmental factors and intent to use narrow AI

Ludmila ZHDANOVA
(corresponding author)
Kwantlen Polytechnic University, Surrey, BC, Canada
Erin SVEINBJORNSON
Ernst & Young LLP, Vancouver, BC, Canada

Abstract. Artificial intelligence is critical in high impact service industry as it has the potential to significantly enhance consumer wellbeing by improving service accuracy, efficiency, and precision. However, the rapid integration of artificial intelligence into the workplace has resulted in fear and anxiety related to implementation, as well as a general dissatisfaction and discontinued usage of the system. In theory, organizational context and policy have a significant impact on user attitudes towards and intent to use artificial intelligence. *Purpose*. This study examined expanded the Technology Acceptance Model using bootstrap mediational analyses on a sample of employees in organizations that utilize narrow artificial intelligence (AI) within the high impact service industry (i.e., healthcare, law, finance) in Canada and the United States. *Method*. The sample (N = 78) consisted of 46.3% males, 49.9% females, and 3.8% who preferred not to say. All participants in the sample were full-time employees, ensuring that each participant had adequate exposure to the organizational norms and practices. Participants for this quantitative correlational study were recruited from organizations who utilize narrow AI or are the system developers of the AI. Interested individuals accessed the survey by using the link in the recruitment materials to an on-line survey hosted on the SurveyMonkey platform. The questionnaire included items about communication climate, AI-communication climate, procedural justice, AI-procedural justice, training and development opportunities, AI training and development opportunities, perceptions of AI system, trust in Narrow AI, direct trust in AI, behavioral intent to use, experience and beliefs in AI. *Findings*. Study results demonstrate that more positive perceptions of procedural justice and communication climate relate to positive perceptions of usefulness and thus, trust in AI which in turn, relates to higher levels of intent to use.

Keywords: artificial intelligence; technology acceptance; change management; trust; communication.

Introduction

Artificial Intelligence (AI) has become a progressive way for organizations to attain a competitive advantage, making AI an essential aspect of many organization's growth strategies (e.g., Kemp, 2023; Krakowski et al., 2022).). AI is predicted to disrupt the organization of job designs and to require

Address: 12666 72 Ave Surrey, BC V3W2M8, Surrey, BC, Canada **E-mail**: Liudmila.jdanova@kpu.ca

additional unique skills and abilities (Cramarenco et al., 2023; Wisskirchen et al., 2017). *Gallup, Inc.* reported 76% of Americans believing that their jobs will fundamentally change due to AI (Gallup, 2018). As a result, many express distrust, concerns, and resistance around the integration of AI into their workplace (Hirsch, 2017). This is problematic of the organizations, since one of the most common reasons for technology, including AI, implementation failure is employee resistance to adaptation of new technologies (e.g., Bérubé et al., 2021). As a result of this resistance, organizations face multiple implementation attempts, employee dissatisfaction with, misuse of, and retaliation against the newly implemented technology, and significant monetary loss and disruption (Karsh, 2004).

As such, researchers have studied technology, including AI, implementation and what predicts end-user acceptance (e.g., Nnaji et al., 2023; Legris et al., 2003; Karsh, 2004). With the focus on implementation design, researchers have demonstrated that organizational environmental factors and policy have impact on the resistance tendencies and implementation outcomes (e.g., Venkatesh, Bala, 2008). Researchers also considered social construction of AI and human interaction by examining perceptions of, trust in, and willingness to use AI (Bacha et al., 2024; Boyd, Holton, 2017; Kipnis, 1996). Technology Acceptance Model (TAM), based on the Theory of Planned Behavior (TPB), is a widely used framework that explains the process of user acceptance and use of technology (Ajzen, 2020; Davis et al., 1989).

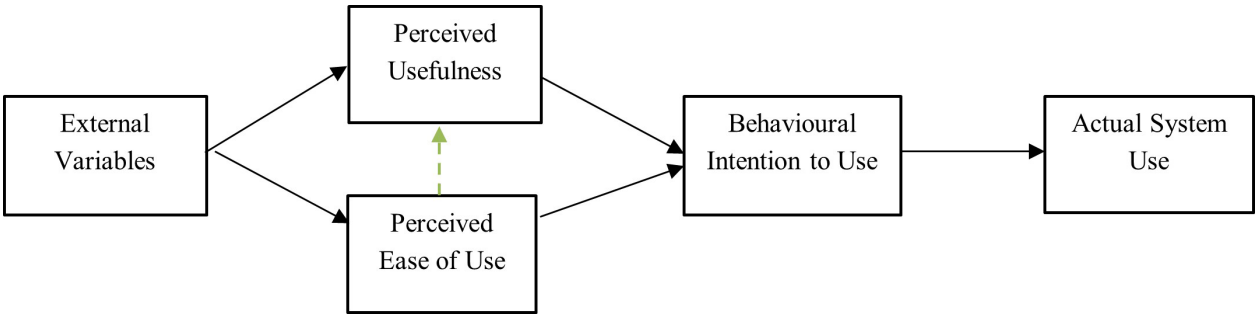

Figure 1. The proposed path for technology usage by F. Davis (1989)

The TAM (Figure 1) suggests that perceptions of a technology's ease of use and usefulness predict end user attitudes towards the system and the subsequent behavioral intent to use (Nnaji et al., 2023). It is theorized that if a technology is perceived as both easy to use and useful, a person is more likely to have a positive attitude towards using a technology, and therefore, a greater intend to and actual use the system (Choung et al., 2023; Davis, 1989). These technology perceptions are formed based on external factors, including technology characteristics (Legris et al., 2003; Nnaji et al., 2023), social influence, and organizational factors (e.g., Legris, et al., 2003; Venkatesh, et al., 2003). These factors can be adjusted to enhance employee perceptions of a technology during implementation design (e.g., Karsh, 2004; Nnaji et al., 2023). While grounded in theory, this model has been found to predict continued usage only some of the time (Buyle, 2018; Nnaji et al., 2023), suggesting there are additional variables missing from the model, with recommendations that trust should be added as a factor that impacts AI usage (e.g., Buyle et al., 2018; Dietvorst, 2015; Holden, Karsh, 2010). The purpose of this study is to examine extended TAM that includes trust as a mediating factor in the relationship between environmental factors, perceptions regarding AI, and intended use of AI.

Theoretical background

Extended technology acceptance model

The TAM adapts the reasoning of TPB that suggests that an attitude towards an act or behavior, perceived behavioral control, and subjective norms lead to a behavioral intent which then determines

actual behavior (Ajzen, 2020). It is theorized that if a technology is perceived as both easy to use and useful, a person will be more likely to have a positive attitude towards using a technology, and therefore, a greater likelihood of intending to use the system (Davis, 1989; Choung et al., 2023). Researchers have also suggested trust as another important variable in this model (e.g., Buyle et al., 2018; Davis et al., 1989; Karsh, 2004; Lee. See, 2004; Tung et al., 2008). Research on algorithm aversion and technology acceptance has found that people develop and value trust in technology in similar ways as they do with other people, suggesting that trust development may mitigate the potential aversion and increase acceptance experienced when using a new AI system (Lee, See, 2004; McClure, 2017).

Trust is considered critical to all relationships (e.g., interpersonal, organizational, technological) with significant effects on behavioral intent and satisfaction (Castelfranchi, Falcone, 2005; Lee, See, 2004; McClure, 2017; Montague et al., 2010). It is especially necessary when there is an interdependence between parties (Kipnis, 1996). In the context of AI implementation, usage is completely reliant on the interdependent nature of the relationship between employees and systems (e.g., Madsen, Gregor, 2000). Trust in AI is the confidence in a successful exchange between two parties, resulting in predetermined and positive outcome (Choung et al., 2023; Muir, 1987). With trust in AI, it is in part a confidence that the system is interpreting the input properly, providing accurate and reliable output and executing on a request as intended. If one trusts that a system is providing truthful and useful output, they will be more apt to utilize that system (Choung et al., 2023; Kipnis, 1996). Thus, based on previous literature on technology acceptance, theory of reasoned action and planned behavior, trust is recommended to be added as a mediator variable in addition to technology perceptions (i.e., ease of use and usefulness) between external variables and intent to use (Figure 2).

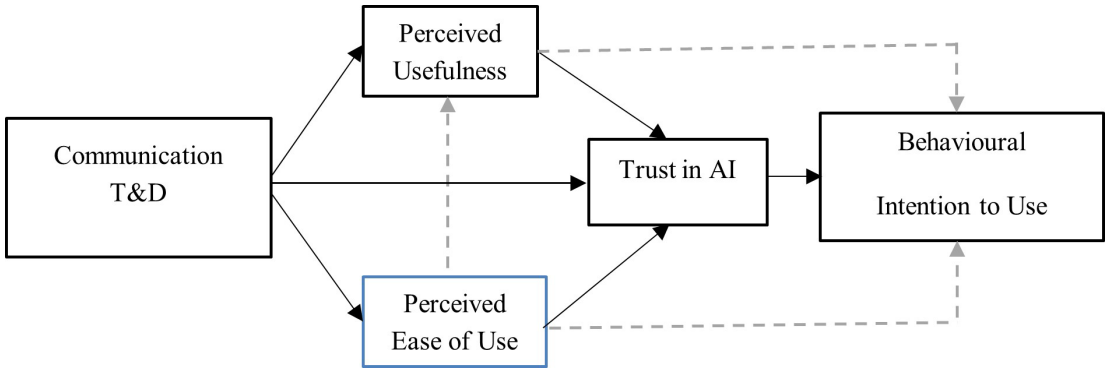

Figure 2. Tested expanded TAM with inclusion of trust

However, research demonstrates lack of trust through strong preference shown by experts and laypeople to trust human based forecasts, not objectively superior AI algorithms' forecasts (e.g., Diab et al., 2011; Gillespie et al., 2023; Promberger, Baron, 2006). Thus, in addition to testing the missing link in the model, this study aims to examine specific organizational factors that can facilitate the development of trust in and positive attitudes towards AI. Both interpersonal and organizational trust literature as well as findings from the TAM and algorithm aversion imply that this trust can be developed through careful design of the of organizational practices and policies that are part of organizational environment (Karsh, 2004; Kipnis, 1996; Madsen, Gregor, 2000; McClure, 2017). Next section reviews literature on specific organizational factors considered in this study.

Organizational environmental factors

Building trust is about forging consistent relationships built on mutual respect and understanding through practices targeted at developing it (Cummings, Bromiley, 1996). It is suggested in multiple

studies and writings, that communication climate, training and development, and procedural justice are all ways of managing and developing trust for human-system interdependence (e.g., Cummings, Worley, 2014; Freimuth et al., 2017; Karsh, 2004; Sagie, Aycan, 2003; Mcknight et al., 2011; Naumann, Bennett, 2000).

Communication climate

Communication climate (CC) refers to employee perceptions regarding the quality of communication within their workplace (Roberts, 2013). It concerns the tone or nature of information exchanges within the workplace, both verbal and non-verbal (Roberts, 2013). A positive communication climate is a stable pattern of adequate, genuine, open, considerate, and participative communication which has been shown to lead to feelings of engagement, credibility, and trust (Barhite, 2018). Communication climate strengthens interpersonal trust due to the transparency of information and the mechanisms in place for feedback and involvement in decisions (Karp, Helgo, 2008). Thus, in a positive communication climate employees are more likely to receive quality communication regarding AI implementation, as well as develop trust.

Procedural justice

Procedural justice (PJ) is defined as the employee's perception regarding the degree of fairness in organizational processes and rules around the treatment of employees (Adamovic, 2023). Research demonstrates positive relationship between PJ with trust (Adamovic, 2023; Saunders, Thornhill, 2003). Based on equity theory, it can be assumed that fair and consistent processes in organizations lead to trust development due to the confidence and predictability of outcomes with equivalence to the input (Pritchard, 1969). Thus, PJ becomes increasingly important for trust development when the severity of outcome is heightened. In relation to AI, employees who perceive organization's procedures and interactions as fair are more likely to have a sense of trust in the decisions to implement and usefulness of AI and thus, be willing to trust in the output of AI, without fear of retaliation if the output results in a negative outcome (Adamovic, 2023; Saunders, Thornhill, 2003; Wang et al., 2020).

Training and development

Training and development (T&D) refer to the ongoing support provided by the organization to coach and enhance employee's knowledge and abilities for growth and future performance success and is critical for the development of efficacy and high performance (e.g., Cascio, Aguinis, 2010). Training perceptions are developed regarding the quality of and satisfaction with organizational training and development initiatives. The evaluation of the training by trainee can differentiate between successful and unsuccessful training initiatives. Organizational support for training, an employee's feelings about training opportunities offered, and an employee's satisfaction with training received are critical for self-trust development because of the linkage between self-efficacy, confidence, and outcome (Bulińska-Stangrecka, Bagieńska, 2021; Schmidt, 2009). In case of AI, employees that are confident that they receive adequate training opportunities are more likely to feel prepared to use the AI system properly, and thus, able to trust in the system output, and are likely to consider using it.

High impact service industry

Trust in AI is especially relevant to the high impact service industry, which is defined as any business that provides a service for a customer or client where the outcome of the work has a significant impact on the well-being of the individual. As a result of the criticality of increased precision, accuracy, and reliability for the welfare of the consumers, there is a significant demand within the high impact service industry to utilize AI for the more robust, technical decisions (Lee,

See, 2004; Mohamed et al., 2019). However, given that the high impact service industry is historically mechanistically structured with strict and formal policies, and long standing, established industry norms, they are generally more likely to struggle with behavioral-social change, including AI implementation, in comparison to organic organizations (Waldersee et al., 2003). The three areas which are already seeing a significant impact due to AI include healthcare, law, and the financial services industry, and thus, are the focus of this research. In addition, this study specifically considers narrow AI. AI has two broad forms: narrow or general (Wisskirchen et al., 2017). General AI is a computer that demonstrates the ability to mimic all functions of human intelligence (Hintz, 2016). In contrast, narrow AI can be defined as the work process of any machine that is able to simulate human intelligence through the investigation of a human process(es) such as problem-solving behavior or learning Today, narrow artificial intelligence in many ways has become the norm to many, with examples ranging from Apple's Siri or Google's Alexa to Uber's self-driving cars (Wisskirchen et al., 2017). Thus, this study considers AI acceptance and intent to use in the context of the high impact service industry.

Current research

Currently, there is little research addressing AI acceptance (Kelly et al., 2023; McClure, 2017). TAM has been a useful framework to guide researchers and practitioners towards understanding factors that impact employee acceptance and use of AI systems. However, the empirical tests of the model have yielded mixed results, pointing to missing factors in the model. Based on change management literature, trust could be one of those factors (McClure, 2017). Although studies have investigated the relationship between trust and organizational practices, there has yet to be extensive research exploring these relationships in the context of trust in AI, specifically with the outcome of system usage (Cummings, Worley, 2014; Freimuth et al., 2017; Mcknight et al., 2011). The current research aims to investigate the role trust plays in employee intent to use narrow AI in the context of the high impact service industry. As a result, this study tests the proposed extended TAM (see Figure 2), which specifies mediating roles of perceived usefulness, ease of use, and trust in AI in the relationship between CC, PJ, and T&D satisfaction with intent to use narrow AI.

Method

Participants

Employees minimum 19-years of age and working full time for longer than 6 months at an organization that utilize narrow AI within the high impact service industry (i.e., healthcare, law, finance) in Canada and the United States were recruited for this study. A total of 94 individuals participated in the study yielding 78 participant data sets (N = 78). Participants were excluded if they did not meet the inclusion criteria outlined in recruitment documents. The sample consisted of 46.3% males (n = 37), 49.9% females (n = 37), and 3.8% who preferred not to say (n = 3). All participants in the sample were full-time employees (N = 78, 100%), ensuring that each participant had adequate exposure to the organizational norms and practices. The sample was represented by 31% of participants aged 19-29 (n = 25), 26% aged 30-39 (n = 21), 20% aged 40-49 (n = 16), 12.5% aged 50-59 (n = 12), and 6% aged 60-69 (n = 5). Participants possessed a diverse range of education achieved, including 40% with a bachelor's degree as their highest level of education (n = 31), 30% with a professional (e.g., MD, JD, PharmD) or doctoral degree (PhD, PsyD, Th.D) (n = 24), 21% with a master's degree (n = 17), 4% with a graduate diploma (n = 3), and 3% with a college diploma (n = 2). Finally, 21% worked in the legal services (n = 17), 18% in healthcare (n = 14), and 61% in financial services (n = 47).

Procedures

The study procedures were approved by the institutional Research Ethics Board. Participants for this quantitative correlational study were recruited from organizations who utilize narrow AI or are the system developers of the AI. The recruitment message was circulated to employees via internal email within each organization. Additionally, participants were recruited through the recruitment poster posted on LinkedIn and Indeed. Interested individuals accessed the survey by using the link in the recruitment materials to an on-line survey hosted on the SurveyMonkey platform. Following the provision of consent to participate, participants were permitted to access the survey. The responses were collected in an anonymous manner, with the right to withdraw from the study. Participants were given an opportunity to enter a draw for a $30.00 Visa gift card.

Measures

Communication climate. Employee perceptions of the communication climate at their workplace were measured using the 18-items Communication Climate Survey (Dennis, 1974). Participants reported level of agreement with statements (e.g., «You can communicate job frustrations to your superior») on a 5-point Likert scale (1 — 'strongly disagree'; 5 — 'strongly agree').

AI–communication climate. One question aimed to understand the satisfaction with the overall quality of communication related to the AI system at their workplace on a 5-point Likert scale (1 — 'strongly disagree'; 5 — 'strongly agree'). It was generated for this study: «Overall you are satisfied with the communication surrounding the narrow AI at your workplace.»

Procedural justice. Participants' procedural justice perceptions were measured with the Workplace Justice Perceptions Measure (Kim, Leung, 2004). While the measure consists of three dimensions (i.e., procedural, distributive, and interpersonal), only the procedural justice dimension (six items in total) was administered. It measures the employees perceived levels of fairness of procedures, utilizing a 7-point Likert scale (1 — 'very strongly disagree'; 7 — 'very strongly agree'). Sample items include: «This organization makes decisions in fair ways.»

AI–procedural justice. Participant fairness perceptions of their organizations AI specific procedures were measured with 1 item generated for the purpose of this study («The way my organization has created AI specific procedures is fair»).

Training and development. Employee perception regarding the amount and quality of previous training and development (T&D) opportunities at their place of work with the Job Training and Job Satisfaction Survey (Schmidt, 2004). Only the job training satisfaction construct questions covering organizational support for training, employee feelings about T&D, and employee satisfaction with training (eleven in total) were utilized in this study. The scale uses a 6-point Likert scale (1 — 'disagree very much'; 6 — 'agree very much'). Sample item is «Overall, the on-the-job training I receive is applicable to my job.»

AI–training and development. Training and development perceptions specific to the AI system were measured utilizing two questions generated for this study aimed at gauging the participants level of satisfaction with the training and development opportunities received related to the AI system. These questions are: «I am satisfied with the training received for the narrow AI system used for my job» and «I am satisfied with the developmental opportunities offered surrounding the narrow AI system used for my job.»

Perceptions of AI system. Both perceptions, "ease of use" and "usefulness" of AI system, were measured utilizing one question each generated for this study, aimed at determining the employee perceptions of AI system ease of use («I believe the narrow AI system at my work is easy to use») and usefulness («I believe the narrow AI system at my work is useful»). This was measured using a 5-point Likert scale (1— 'strongly disagree'; 5 — 'strongly agree').

Trust in Narrow AI. Given lack of scales that measure trust in AI, this study used an adapted version of the Trust in Specific Technology Scale (McKnight et al., 2011). The original scale measures perceptions of trust in Excel; however, in this study, each item was adapted, substituting 'Excel' with 'narrow AI system'. This 14-item scale utilizes a 5-point Likert scale (1 — 'strongly disagree'; 5 — 'strongly agree'). There are two subscales: 1) trusting belief in a specific technology («The artificial intelligence at my work is a very reliable system»), and 2) situational normality («The artificial intelligence at my work has the functionality I need.» (McKnight et al., 2011). However, in this study, only overall scores were utilized.

Direct trust in AI. To measure the level of direct trust in the output of the AI system utilized at their workplace, one question was generated for this study: «I trust the output from the artificial intelligence system at my work».

Behavioral intent to use. Participant intent to use was measured utilizing one question sourced from Karsh (2004). A 5-point Likert scale (1 — 'strongly disagree'; 5 — 'strongly agree') was utilized to measure participant intent to use the AI system («I intend to use the artificial intelligence system at my work every opportunity I get»).

Experience and beliefs in AI. Experience and belief in AI questionnaires have been measured to control for possible confounding effects of these experiences. Participants were asked 16 questions about the industry and department they work in, their role, job status, tenure, the AI system used at their company, system implementation information, prior experience working with AI, type of contact with AI, frequency of use, consequences of malfunction, and implementation effects.

Results

Table 1 presents descriptive statistics for all study variables, including potential confounding variables measured. Results demonstrated that the two versions (i.e., general and AI specific) of organizational environment factors were highly correlated (above .70), indicating that employee perceptions of general organizational environment factors were in alignment with AI specific perceptions. Preliminary, hypotheses were tested with the perceptions regarding general and AI specific environmental factors and yielded matching results. Given conceptual and statistical overlap (multicollinearity and matching results), perceptions of general and AI specific environment factors were not analyzed together and only results for general organizational environment factors are reported. Confounding variables collected were not related to the outcomes, and therefore, not included as controls in the following analyses.

Table 1. Descriptive statistics and reliability coefficients (on a diagonal)

Variables	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Trust in AI	3.64	.65	(.89)												
2. Direct trust	3.51	1.08	.74	—											
3. Communication climate	3.62	.86	.39	.43	(.96)										
4. AI Communication climate	3.58	1.06	.37	.49	.71	—									
5. Training and development	4.08	.80	.28	.29	.52	.40	(.93)								
6. AI-training and development	3.73	1.10	.28	.45	.45	.52	.71	(.73)							
7. Procedural justice	5.08	.85	.29	.34	.35	.27	.20	.23	(.90)						
8. AI-procedure justice	4.85	1.05	.47	.58	.33	.38	.14	.32	.62	(.87)					
9. Usefulness	4.65	.55	.61	.58	.27	.32	.12	.17	.20	.26	—				
10. Ease to use	3.90	.88	.24	.19	.10	.15	.23	.12	–.18	.03	.29	—			
11. Intent	3.85	1.19	.73	.83	.43	.45	.25	.38	.35	.53	.67	.26	—		
12. Age	—	—	–.09	–.18	–.01	–.03	.14	.01	.01	–.12	–.29	–.08	–.24	—	
13. Gender	—	—	–.04	–.11	–.10	–.05	–.12	–.16	–.35	–.25	–.15	–.03	–.06	.02	—

Notes. $N = 78$; a Gender: 1 = male, 2 = female; $p < .05$; $p < .01$. The dash is in lieu of coefficient is for a 1-item or categorical measure.

Mediational analyses

Due to the small sample size, the bootstrap mediational analyses (Preacher, Hayes, 2008) were utilized in this study in lieu of Structural Equation Modeling. The analysis yields estimate of indirect effects, standard errors, confidence intervals, and the regression coefficients, based on the estimates from 5,000 samples drawn with replacement from the data. Significance of indirect effect is concluded when the 95% confidence interval does not include a zero (Preacher, Hayes, 2008). In this study, the first set of analyses was conducted using parallel mediation approach. Specifically, three mediational analyses were conducted, with one of the organizational environment factors (i.e., communication climate, procedural justice, T&D satisfaction) as a predictor, the technology perceptions (i.e., ease of use, usefulness) and trust in AI as concurrent mediators, and behavioral intent to use as an outcome. The results of this set of analyses informed the following model testing by identifying significant relationships.

Parallel multiple mediation model

Total effect of communication climate on intent to use was significant (total effect = .60, $p < .01$; Figure 3), but not direct effect (direct effect = .21, $p = .05$) when three mediators, ease of use, usefulness and trust in AI were entered into the equation. Usefulness ($\beta = .72$, $p < .01$) and trust in AI ($\beta = .87$, $p < .01$) significantly predicted intent to use, while ease of use did not. Indirect effects of communication climate on intent to use through usefulness (indirect effect = .13, BC α CI [.03, .25], $p < .05$) and trust (indirect effect = .25, BC α CI [.16, .62], $p < .05$) were significant.

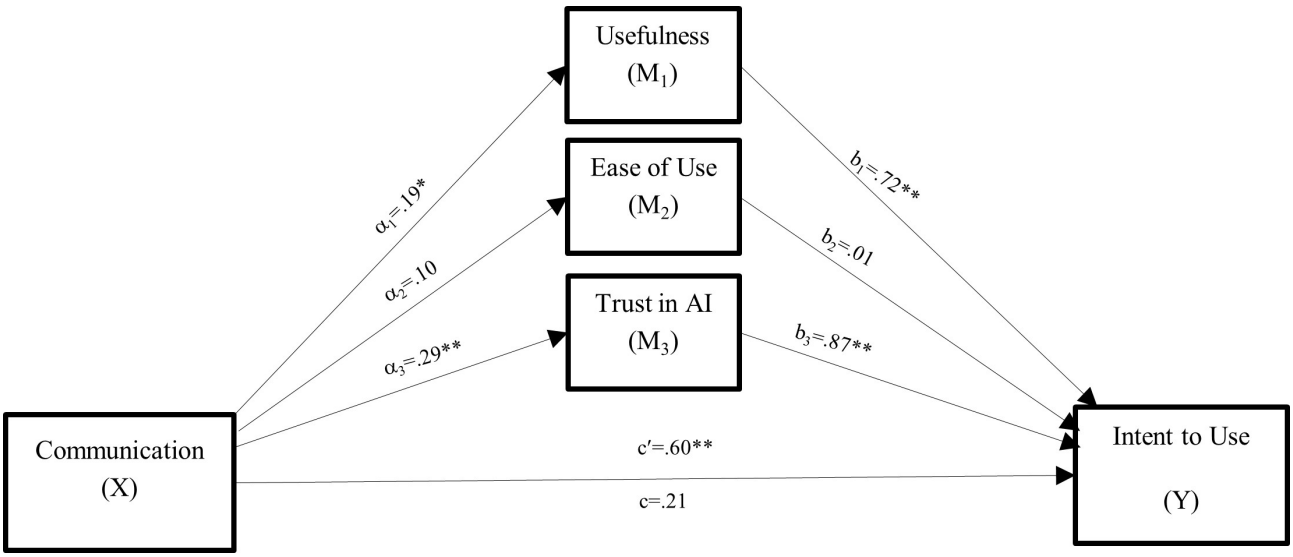

Figure 3. Parallel mediation model of communication climate on intent to use

The total effect of T&D satisfaction on intent to use was significant (total effect = .35, $p < .05$; Figure 4), but not direct effect (direct effect = .08, $p = .45$), when three mediators were entered into the equation. Usefulness ($\beta = .76$, $p < .01$) and trust in AI ($\beta = .93$, $p < .01$) also significantly predicted intent to use, while ease of use did not. T&D satisfaction did not predict the technology usefulness and ease perceptions. A significant indirect effect of T&D satisfaction on intention to use through trust (indirect effect = .20, BC α CI [.04, .42], $p < .05$) was revealed.

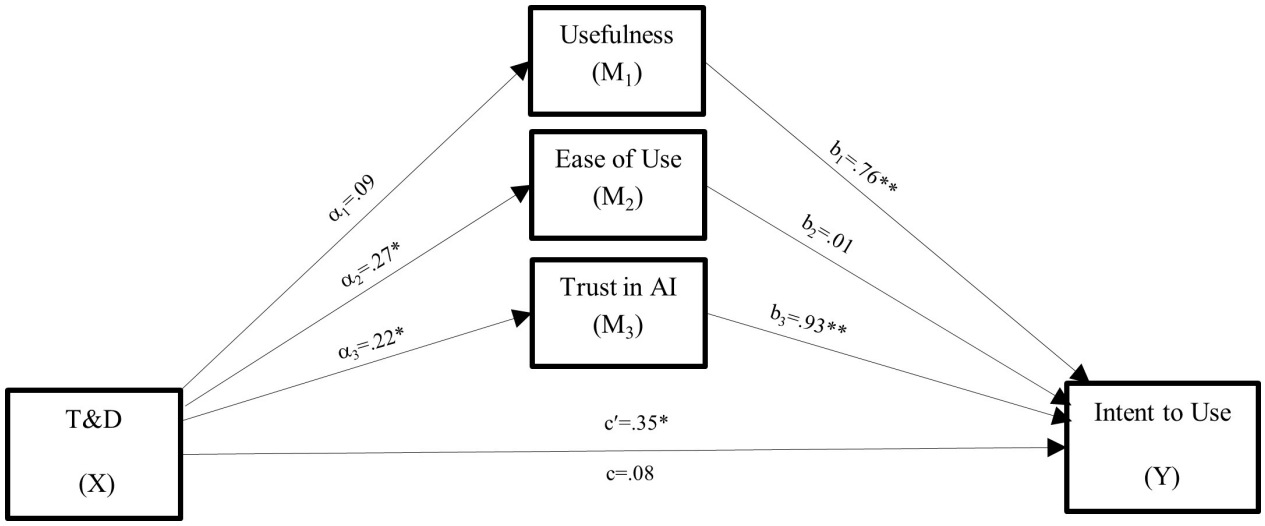

Figure 4. Parallel mediation model of T&D on intent to use

The total effect of PJ on intent to use was significant (total effect = .50, $p < .01$; Figure 5), but not direct effect (direct effect = .21, $p = .05$) when three mediators were entered as predictors. Usefulness ($\beta = .69$, $p < .01$) and trust in AI ($\beta = .90$, $p < .01$) significantly predicted intent to use, while ease of use did not. Indirect effects of PJ on intent to use through usefulness (indirect effect = .11, BC α CI [.02, .24], $p < .05$) and trust (indirect effect = .20, BC α CI [.04, .37], $p < .05$) were significant.

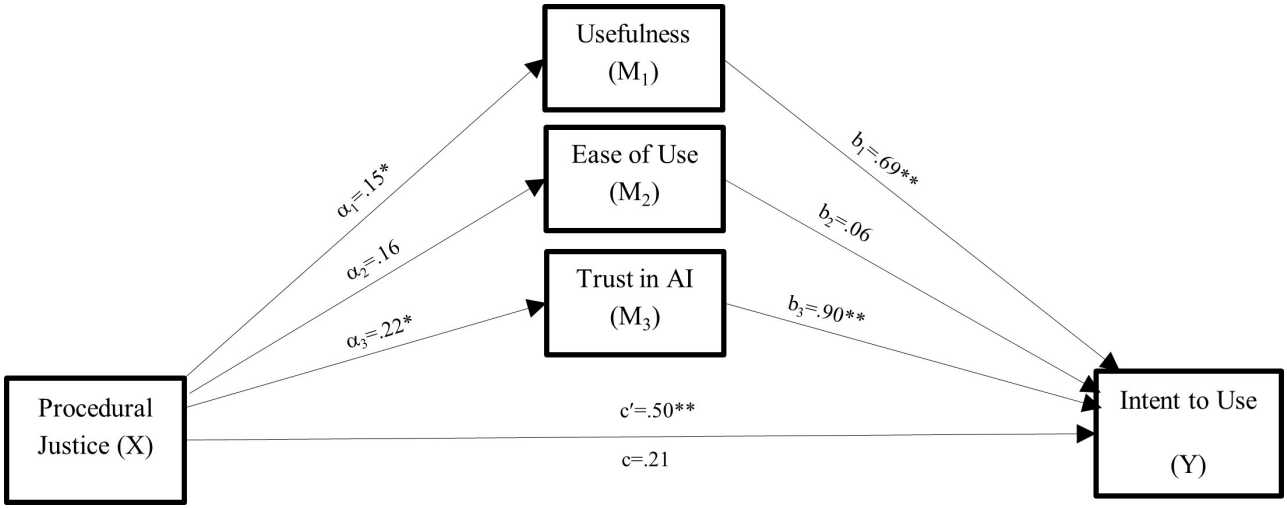

Figure 5. Parallel mediation model of procedural justice on intent to use

The results indicated that usefulness and trust in AI are mediators in the relationship between communication climate and PJ with intent to use. T&D satisfaction did not predict either of the perceptions of AI. Thus, the proposed model was tested with usefulness and trust in AI as serial mediators with communication climate and PJ as predictors.

Serial multiple mediation model. Results from the first serial multiple mediational analysis (Figure 6) showed support for the model that presents usefulness and trust serving as sequential mediators of the relationship between communication climate and intent to use. Communication climate increased intent to use serially through increased usefulness, and subsequently, increased trust in AI (a1a3b2: indirect effect = .09, BC α CI [.02, .18], $p < .05$). In addition, an indirect effect (X→M1→Y) was discovered for communication climate on intent to use through usefulness (a1b1: indirect effect =

.11, BC α CI [.02, .21], $p < .05$) and trust in AI (X→ M2 →Y; a3b2: indirect effect = .13, BC α CI [.13, .26], $p < .05$). Finally, the analysis revealed that there was a significant total indirect effect of communication climate on intent to use through usefulness and trust in AI (total indirect effect = .39, BC α CI [.16, .62], $p < .05$). When the mediators, usefulness and trust in AI were entered into the equation, there was no evidence of a direct effect of communication climate on intent to use (direct effect = .21, $p = .05$). Results support the extended TAM with trust as an added variable and communication climate as an organizational environmental factor. Specifically, employees with more positive perceptions of communication climate were more likely to have more positive perceptions of usefulness and thus, higher levels of trust in AI which in turn, resulted in higher levels of intent to use.

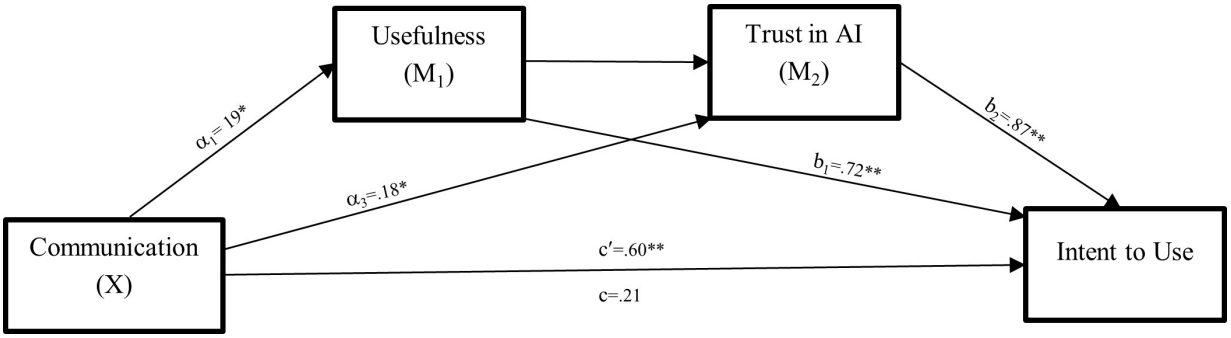

Figure 6. Serial mediation model of communication climate on intent to use

Results from the second serial multiple mediational analysis (Figure 7) demonstrated serial mediation with usefulness and trust serving as mediators between procedural justice and intent to use. Procedural justice increased intent to use serially through increased usefulness, and subsequently, increased trust in AI (a1a3b2: indirect effect = .09, BC α CI [.02, .19], $p < .05$). In addition, an indirect effect (X→M1→ Y) was discovered for procedural justice on intent to use through usefulness (a1b1: indirect effect = .11, BC α CI [.02, .24], $p < .05$). However, an indirect effect (X→M2→Y) was not found for procedural justice on intent to use through trust (a3b2: indirect effect = .11, BC α CI [–.03, .25], $p < .05$).

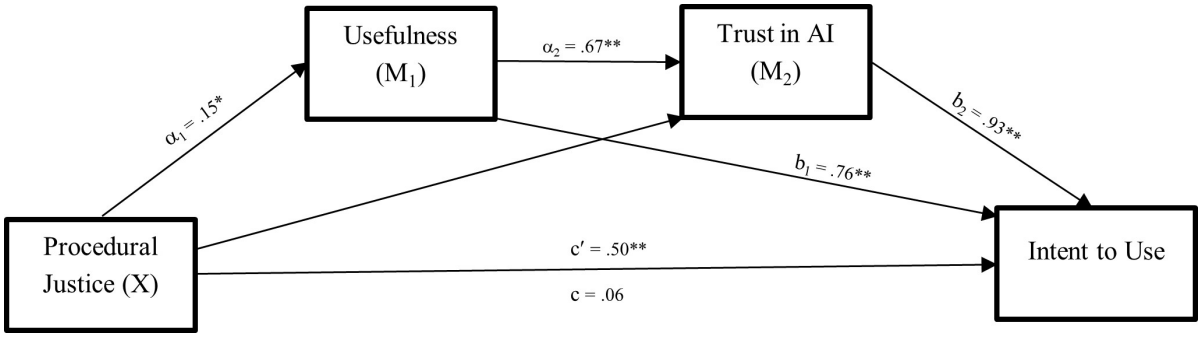

Figure 7. Serial mediation model of procedural justice on intent to use

Finally, the analysis revealed that there was a significant total indirect effect of procedural justice on intent to use through usefulness and trust in AI (total indirect effect = .31, BC α CI [.09, .54], $p < .05$). When the mediators, usefulness and trust in AI were entered into the equation, there was no evidence of a direct effect of procedural justice on intent to use (direct effect = .20, $p = .06$). Results support the extended TAM with procedural justice as an organizational environmental factor. Specifically, employees with more positive perceptions of procedural justice were more likely to have more positive perceptions of usefulness and thus trust in AI which, in turn, resulted in higher levels of intent to use.

Discussion

This study aimed to add to the AI implementation and change management literature through examination of the environmental factors that facilitate positive perceptions and trust in narrow AI, minimizing employee resistance to AI within the high impact service industry. The technology acceptance model was expanded to incorporated trust, along with previously considered AI perceptions. The impact of environmental factors (communication climate, training and development satisfaction, and procedural justice) on trust and AI perceptions, with the subsequent impact on intent to use the AI, was examined.

Consistent with theory and research, positive perceptions of communication climate, T&D satisfaction, and PJ were associated with higher levels of trust in the AI system (e.g., Karp, Helgo, 2008; Kipnis, 1996; Saunders, Thornhill, 2003). Communication within an organization has been proposed to enhance trust by altering mental representations through explanations and PDM (Castelfranchi, Falcone, 2005). Previous research reports that when treated fairly, employee attitudes and behaviors essential for support of large-scale change, including technology implementation, were enhanced (Karsh, 2004; Saunders, Thornhill, 2003). In relation to T&D satisfaction, TPB suggests that an individual's perceived self-efficacy (they can execute properly on requirements) and behavioral control (proper execution will lead to expected outcomes) results in confidence in an outcome and action (Hagger, Hamilton, 2024). Thus, this study provides further evidence that positive communication climate, PJ, and T&D satisfaction are critical for AI trust and acceptance.

Results of the preliminary set of analyses that considered both technology perceptions (i.e., ease of use, usefulness) and trust in AI simultaneously as mediators, revealed that perceptions of ease of use did not appear to be a significant mediator in any of the relationships. Usefulness was shown to meditate both communications climate and procedural justice with intent to use. Trust was shown to mediate the relationship for all three examined environmental factors with intent to use. The results support propositions and preliminary findings from previous studies within similar industries suggesting trust as a critical factor in the expansion of the TAM (e.g., Tun et al., 2008).

However, perceptions regarding the ease of use are part of the TAM, as it was not predicted by any of the environmental factors, nor predicted intent to use. This finding aligned with previous exploratory research conducted by F. Calisir and colleagues that demonstrated that ease of use is less important for implementation outcomes in the context of enterprise resource planning systems (ERP), than compatibility with the system and employee requirements (Calisir et al., 2009). They concluded that if the system is not compatible with employee needs and requirements, they will not be inclined to utilize the system regardless of whether they perceive it as easy to use or not (Calisir et al., 2009).

One potential reason for why ease of use did not relate to intent to use AI could be due to the specific industries analyzed. Participants were specifically recruited from the high impact service industry, with notable implications for their consumer if failure occurs. As a result, it is possible that ease of use is not a concern, but rather accuracy and usefulness of the system is the focus to avoid failures. It is possible that if employees believe it is useful and will help other people, they might be more willing to overlook the complexities of technology and embrace the challenge of learning and use it to benefit from its use. Alternatively, employees might conclude that easy to use technology is not capable of accurately performing a task that would normally be considered a very complex task to a human. The representation of younger (55% younger than 40) and highly educated (minimum a bachelor's degree with a large portion of them having attained doctoral degrees) participants could also contribute to these results. These participants are likely to have exposure to and experience with technology and thus to understand and master the system quickly, which research shows both lend to positive ease of use perceptions or giving less importance to this aspect (Karsh, 2004; Lee, See, 2004).

This study did not examine whether the technology usage was mandatory or flexible at the participant's place of work or role. Prior research on the TAM have shown that usefulness typically has stronger mediational potential within the model, when the technology usage is not mandatory (Karsh, 2004). In contrast, when technology usage is mandatory, ease of use becomes a more important component of the model (Karsh, 2004). In addition, ease of use may become less important to an individual overtime. Once an individual has utilized the technology for some time, ease of use perceptions will increase and become less important (Karsh, 2004).

The relationship between T&D satisfaction and intent to use AI was not mediated by either ease of use or usefulness when considered in parallel with trust in AI, with T&D satisfaction not predicting usefulness perceptions. Thus, it appears that T&D satisfaction does not impact technical perceptions of AI but develops trust in AI and its output. Results from a study done on nurses receiving training for computer technology reported low satisfaction with T&D opportunities due to the demanding nature of their job, reducing the amount of free time they must complete training, particularly if the training is voluntary (Eley, et al., 2008). Thus, it is possible that, given that the high impact service jobs are demanding, there was a lack of sufficient time to engage in training. In addition, this study only measured level one, i.e., reactions, in Kirkpatrick Model of training evaluation (Kirkpatrick, 1996), which in literature has been demonstrated to be the least indicative of training effectiveness (Tamkin et al., 2002). Other levels Training effectiveness related to the AI system, such as actual learning and behavioral change, were not measured. As a result, it is possible that people were reporting high levels of satisfaction with their learning, but did not increase their efficacy and competencies related to system usage, thus, not increasing their ease of use or usefulness perceptions.

Results for the analyses of the extended TAM model that places showed support for extended TAM model with usefulness and trust acting as full sequential mediators in the relationship both between communication climate and procedural justice with intent to use. The environmental factors predicted usefulness, which in turn predicted trust in AI, which resulted in an intent to use the AI system. These findings were in line with prior research on the TAM as well as results previously discussed in this study (Davis, 1989; Fishbein, Ajzen, 1975).

Conclusion

To conclude, the expanded TAM was tested, adding trust in AI as a mediator in the relationship between environmental factors and intent to use. Analyses revealed that usefulness and trust in AI act as sequential mediator variables in the relationship between environmental factors (i.e., communication climate and procedural justice) and behavioral intent to use the narrow AI. Thus, change practitioners should focus on trust in AI development by utilizing the environmental factors as leverage and designing implementation process with consideration of communication climate and fair processes and procedures. While there is no 'one size fits all' solution to the phenomena of algorithm aversion, trust in AI appears to be an important factor to consider in encouraging the use of AI. The findings of this study serve as a baseline to future research on the topic of AI implementation and change management tactics. It provides an expanded, more appropriate TAM for AI specifically and provides recommendations for improvement. It confirms past researchers' suggestions to analyze trust and provides a start to understanding what organizational environment components can be utilized to drive trust development in AI to promote usage.

Implication

Theoretically, based on results from this research, the expanded TAM is partially supported, and should further be explored. Environmental factors were positively correlated with AI specific

environmental factors as well as ease of use, usefulness, trust in AI and intent to use. Further exploration confirmed previous research on technology implementation, trust development, and change management theory (e.g., Davis 1989; Karsh, 2004; Cummings, Worley, 2014). Suggestions to introduce trust in AI into the model as one of the key attitudinal components that predict intent to use AI were supported.

This study also offers important practical considerations for organizations preparing for AI implementation. These findings emphasize the importance of considering broader organization-wide implementation tactics focused on communication climate and procedural justice. It is advised to actively develop practices conducive to participative decision-making, sufficient and supportive interpersonal relationships, progressive T&D opportunities, and just procedures through practices such as clear and transparent governance structures. Given that these general practices impacted specific AI initiatives, these practices should be present throughout the employee lifecycle, from inception to offboarding and alumni management.

Focusing on participative decision-making and transparency, timely communication throughout all practices and periods of change is a key component of ensuring fair and just practices and trust. A specific communications plan should be developed to target diverse stakeholder groups ensuring awareness and desire of the upcoming changes with a focus on system usefulness and efficacy. Selecting and promoting a system that is easy to use should come secondary and only when the system usage is mandated and not conducting a complex task. Activity assessments may be conducted to understand current processes against future design and provide opportunity to solicit feedback and jointly develop future design criteria and policy. The initiatives to enhance ease of use and usefulness, ensuring the highest potential for trust in AI should be implemented prior and during the AI implementation.

Limitations and future considerations

There are several limitations to this study that present opportunities for future research. The first limitation concerns sample size, which presents concerns with examining and controlling for potential group differences, such as based on the diverse geographical location represented in the sample. Comparing those working within healthcare, law or finance or who used the same AI system were not possible as well. Future research should be conducted on a larger sample size, as well as examine the potential effect of specific geographical regions, industry, or AI system. In addition, small sample size also did not allow the use of Structural Equation Modeling to test the extended TAM with all three environmental factors simultaneously. Second, this study utilized self-reported cross-sectionally collected data, given that measured constructs were specifically enquiring about employee perceptions and intentions. Thus, common method variance is a potential concern.

A third limitation concerns utilization of one-item scales to measure participant AI specific perceptions. This limitation is based on lack of valid and reliable multiitem scales that measure employee perceptions of AI. In the future, researchers should create and validate scales differentiating between the general organizational drivers (communication climate, training and development, and organizational justice) and the specific drivers linked to the AI implementation to minimize potential overlap and multicollinearity. In addition, the Trust in AI scale was modified from the Trust in a Specific Technology Scale. Because AI and technology are very similar, the scale conceptually works for the exploratory nature of this study.

Fourth, due to the complexity of trust as a construct, the lack of control for potential confounds is a noteworthy limitation to address in future research. An individual's predisposition towards trusting behavior and the situational and environmental trust, learned trust, and organizational trust are likely confounding variables in the human-AI relationship. For example, if an employee has a

natural predisposition to trust easily in general, then it will be likely that that individual also trusts in the AI system, regardless of the climate variable perceptions. It is important to consider these factors in future research, controlling for potentially confounding affects resulting from these variables. In addition, levels of trust may vary with time spent with a system and therefore, a longitudinal study may be considered to better understand how the lifecycle changes as one works with the system over time. Finally, this study utilized intent to use as an outcome. While theory of planned behavior suggests that an intent is a good predictor of behavior (Hagger, Hamilton, 2024), actual behavioral outcome (use of AI systems), should be studied, along with boundary conditions that impact the relationship between intent to use and actual use of AI.

References

Adamovic, M. (2023). Organizational justice research: A review, synthesis, and research agenda. *European Management Review*, 20(6), https://doi.org/10.1111/emre.12564

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies, 2*(4), 314–324. https://doi.org/10.1002/hbe2.195

Bacha, T. A., Khan, A., Hallock, H., Beltrão, G., Sousa, S. (2024). A systematic literature review of user trust in AI-enabled systems: An HCI perspective. *International Journal of Human–Computer Interaction, 40*(5), 1251–1266. https://doi.org/10.1080/10447318.2022.2138826

Barhite, B. (2018). The effects of virtual leadership communication on employee engagement (Doctoral dissertation). Available from PsycINFO. (10645430)

Bérubé, M., Giannelia, T., Vial, G. (2021). Barriers to the implementation of AI in organizations: Findings from a Delphi study. *Proceedings of the Hawaii International Conference on System Sciences*. https://doi.org/10.24251/HICSS.2021.805

Boyd, R., Holton, R. (2017). Technology, innovation, employment and power: Does robotics and artificial intelligence really mean social transformation? *The Journal of Sociology, 54*(3), 331–345. https://doi.org/10.1177/1440783317726591

Bulińska-Stangrecka, H., Bagieńska, A. (2021). The impact of employee training and development on tacit knowledge transfer and the mediating role of trust. *International Journal of Learning and Change*, *13*(5), 474–489. https://doi.org/10.1504/IJLC.2021.116668

Buyle, R., Van Compernolle, M., Vlassenroot, E., Vanlishout, Z., Mechant, P., Mannens, E. (2018). "Technology readiness and acceptance model" as a predictor for the use intention of data standards in smart cities. M*edia and Communication, 6*(4), 127–139.

Calisir, F., Gumussoy, C., Bayram, A. (2009). Predicting the behavioral intention to use enterprise resource planning systems: An exploratory extension of the technology acceptance model. *Management Research News, 32*(7), 597–613. doi:10.1108/01409170910965215

Cascio, W., Aguinis, H. (2010). *Applied psychology in human resource management* (7th ed.). Boston, MA: Prentice Hall.

Castelfranchi, C., Falcone, R. (2005). Socio-cognitive theory of trust. London, England: Wiley.

Choung, H., David, P., Ross, A. (2023). Trust in AI and its role in the acceptance of AI technologies. *International Journal of Human–Computer Interaction, 39*(9), 1727–1739.

Cramarenco, R. E., Burcă-Voicu, M. I., Dabija, D.-C. (2023). The impact of artificial intelligence (AI) on employees' skills and well-being in global labor markets: A systematic review. *Oeconomia Copernicana, 14*(3), 731–767. https://doi.org/

Cummings, T., Worley, C. (2014). *Organization development and change* (10th ed.). Mason, OH: South-Western.

Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Davis, F., Bagozzi, R., Warshaw, P. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

Dennis, H. (1974). *A theoretical and empirical study of managerial communication climate in complex organizations* (Unpublished doctoral dissertation.). Purdue University, West Lafayette, IN.

Diab, D. L., Pui, S. Y., Yankelevich, M., Highhouse, S. (2011). Lay perceptions of selection decision aids in U.S. and non-U.S. samples. *International Journal of Selection and Assessment, 19*, 209–216. http:// dx.doi.org/10.1111/j.1468-2389.2011.00548.x

Dietvorst, B., Simmons, J., Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 144*(1), 114–126. https://doi.org/10.1037/xge0000033

Freimuth, V., Jamison, A., An, J., Hancock, G., Quinn, S. (2017). Determinants of trust in the flu vaccine for African Americans and Whites. *Social Science & Medicine, 193*, 70–79. doi:10.1016/j.socscimed.2017.10.001

Gallup. (2018). *Optimism and anxiety: Views on the impact of artificial intelligence and higher education's response*. Washington, DC: Author. Retrieved from https://www.northeastern.edu/gallup/pdf/OptimismAnxietyNortheasternGallup.pdf

Gillespie, N., Lockey, S., Curtis, C., Pool, J., Akbari, A. (2023). *Trust in artificial intelligence: A global study*. The University of Queensland and KPMG Australia. doi: 10.14264/00d3c94

Hagger, M. S., Hamilton, K. (2024). Longitudinal tests of the theory of planned behaviour: A meta-analysis. *European Review of Social Psychology, 35*(1), 198–254.
https://doi.org/10.1080/10463283.2023.2225897

Hirsch, P. (2017). The robot in the window seat. The Journal of Business Strategy, 38(4), 47–51.

Holden, R., Karsh, B. (2010). The technology acceptance model: Its past and its future in health care. Journal of Biomedical Informatics, 43(1), 159–172. https://doi.org/10.1016/j.jbi.2009.07.002

Karsh, B. (2004). Beyond usability: designing effective technology implementation systems to promote patient safety. BMJ Quality & Safety, 13(5), 388–394. doi:10.1136/qhc.13.5.388

Karp, T., Helgø, T. (2008). The future of leadership: The art of leading people in a "post-managerial" environment. Foresight, 10(2), 30–37. doi:10.1108/14636680810869662.

Kelly, S., Kaye, S.-A., Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics, 77*, 101925. https://doi.org/10.1016/j.tele.2023.101925

Kemp, A. (2023). Competitive advantage through artificial intelligence: Toward a theory of situated AI. *Academy of Management Review, 49*(3), 543–563. https://doi.org/10.5465/amr.2020.0205

Kim, T., Leung, K. (2004). *Workplace Justice Perceptions Measure* [Database record]. https://doi.org/10.1037/t24229-000

Kipnis, D. (1996). Trust and technology. In R. Kramer and T. Tyler (Eds.), *Trust in organizations: Frontiers of theory and research*. Thousand Oaks, CA: Sage. https://doi.org/10.4135/9781452243610.n3

Kirkpatrick, D. (1996). Revisiting Kirkpatrick's four-level-model. *Training & Development, 1*, 54–57.

Krakowski, S., Luger, J., Raisch, S. (2022). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal*, *43*(2), 413–433. https://doi.org/10.1002/smj.3387

Lee, J., See, K. (2004). Trust in automation: Designing for appropriate reliance. *The Journal of Human Factors and Ergonomics Study, 46*(1), 50–80. doi:10.1518/hfes.46.1.50_30392

Legris, P., Ingham, J., Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management, 40*(3), 191–204. doi:10.1016/S0378-7206(01)00143-4.

Madsen, M., Gregor, S. (2000). Measuring human-computer trust. In *11th Australasian conference on information systems. Vol. 53* (6–8). Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.93.3874&rep=rep1&type=pdf

McClure, P. (2017). "You're fired," Says the robot: The rise of automation in the workplace, technophobes, and fears of unemployment. *Social Science Computer Review, 36*(2), 139–156. https://doi.org/10.1177/0894439317698637

McEachan, R., Conner, M., Taylor, N., Lawton, R. (2011). Prospective prediction of health-related behaviours with the theory of planned behaviour: A meta-analysis. *Health Psychology Review, 5*(2), 97–144.

Mcknight, D., Carter, M., Thatcher, J., Clay, P. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on Management Information Systems (TMIS), 2*(2), 12.

Montague, E., Winchester, W., Kleiner, B. (2010). Trust in medical technology by patients and healthcare providers in obstetric work systems. *Behaviour & Information Technology, 29*(5), 541–554. doi:10.1080/01449291003752914

Muir, B. (1987). Trust between humans and machines, and the design of decision aids. *International Journal of Man-Machine Studies, 27*(5–6), 527–539. https://doi.org/10.1016/S0020-7373(87)80013-5

Naumann, S., Bennett, N. (2000). A case for procedural justice climate: Development and test of a multilevel model. *Academy of Management journal, 43*(5), 881–889.

Nnaji, C., Okpala, I., Awolusi, I., Gambatese, J. (2023). A systematic review of technology acceptance models and theories in construction research. *Journal of Information Technology in Construction (ITcon), 28*, 39–69. https://doi.org/10.36680/j.itcon.2023.003

Promberger, M., Baron, J. (2006). Do patients trust computers? *Journal of Behavioral Decision Making, 19*, 455–468. http://dx.doi.org/10.1002/ bdm.542

Preacher, K., Hayes, A. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40,* 879–891.

Pritchard, R. (1969). Equity theory: A review and critique. *Organizational Behavior and Human Performance, 4*, 75–94.

Roberts, J. (2013). *Relationships among employee engagement, communication climate, and employees communication channel preferences* (Unpublished doctoral dissertation). Wright State University, Dayton, OH.

Sagie, A., Aycan, Z. (2003). A cross-cultural analysis of participative decision-making in organizations. *Human Relations, 56*(4), 453–473. doi:10.1177/0018726703056004003

Saunders, M., Thornhill, A. (2003). Organisational justice, trust and the management of change: An exploration. *Personnel Review, 32*(3), 360–375. https://doi.org/10.1108/00483480310467660

Schmidt, S. (2004). *The Job Training and Job Satisfaction Survey technical manual*. Unpublished manuscript, East Carolina University.

Schmidt, S. (2009). Employee demographics and job training satisfaction: The relationship between dimensions of diversity and satisfaction with job training. *Human Resource Development International, 12*(3), 297–312. https://doi.org/10.1080/13678860902982082

Tamkin, P., Yarnall, J., Kerrin, M. (2002). *Kirkpatrick and beyond: A review of model of training evaluation*. Brighton, England: Insitute for Employement Studies.

Venkatesh, V., Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., Morris, M., Davis, G., Davis, F. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Wang, G. S., Liu, X. Q., Wang, Z. G., Yang, X. L. (2020). Research on the influence of interpretability of artificial intelligence recommendation system on users' behavior intention. *Proceedings of the 2020 4th International Conference on Electronic*. https://dl.acm.org

Wisskirchen, G., Biacabe, B., Bormann, U., Muntz, A., Niehaus, G., Soler, G., Brauchitsch von, B. (2017). *Artificial intelligence and robotics and their impact on the workplace*. London, England: IBA Global Employment Institute.

Received 03.03.2025

Расширение модели принятия технологий: доверие как посредник во взаимосвязи между факторами окружающей среды и намерением использовать специализированный искусственный интеллект

ЖДАНОВА Людмила
(ответственный автор)
Политехнический университет Квантлен, графство Суррей, Британская Колумбия, Канада

СВЕЙНБЬОРНСОН Эрин
ТОО Эрнст энд Янг, Ванкувер, Британская Колумбия, Канада

Аннотация. Искусственный интеллект играет решающую роль в сфере услуг с высоким уровнем воздействия, поскольку он может значительно улучшить благополучие потребителей за счёт повышения точности, эффективности и достоверности обслуживания. Однако быстрая интеграция искусственного интеллекта в рабочую среду привела к страху и тревоге, связанным с его внедрением, а также к общей неудовлетворённости и отказу от использования ИИ. Теоретически, организационный контекст и политика оказывают существенное влияние на отношение пользователей к искусственному интеллекту и их намерение его использовать. *Цель*. В этом исследовании изучалась расширенная модель принятия технологий с использованием бутстрап-медиационного анализа на выборке сотрудников организаций, которые используют специализированный искусственный интеллект (*narrow AI*)[1] в сфере услуг с высоким уровнем влияния (например, здравоохранение, юриспруденция, финансы) в Канаде и Соединённых Штатах. *Метод*. Выборка (N = 78) состояла из 46,3% мужчин, 49,9% женщин и 3,8% тех, кто предпочёл не указывать свой пол. Все участники выборки были штатными сотрудниками, что гарантировало каждому участнику адекватное знакомство с организационными нормами и практиками. Участники этого количественного корреляционного исследования были набраны из организаций, которые используют специализированный ИИ или являются разработчиками систем ИИ. Заинтересованные лица получили доступ к опросу, используя ссылку в материалах для набора на онлайн-опрос, размещённый на платформе Survey-Monkey. Анкета включала вопросы о коммуникационном климате, ИИ-коммуникационном климате, процессуальной справедливости, ИИ-процессуальной справедливости, возможностях обучения и развития, ИИ-возможностях обучения и развития, восприятии системы ИИ, доверии к специализированному ИИ, прямом доверии к ИИ, поведенческом намерении использовать ИИ, опыте и убеждениях в отношении ИИ. *Результаты*. Результаты исследования показывают, что более позитивное восприятие процессуальной справедливости и коммуникационного климата связано с позитивным восприятием полезности и, следовательно, с доверием к ИИ, что, в свою очередь, связано с более высоким уровнем намерения использовать ИИ.

Ключевые слова: искусственный интеллект; принятие технологий; управление изменениями; доверие; коммуникация.

1 Специализированный (узкий, слабый) искусственный интеллект (англ. *narrow AI*) — система, разработанная для выполнения конкретных задач в ограниченной области. Примеры: системы распознавания изображений и лиц, чат-боты и разговорные помощники, беспилотные автомобили и т.п. — ***Прим. ред.***