7-8-2023

AI Aversion: A Task Dependent Multigroup Analysis

Md Jabir Rahman
The University of Memphis, jabir.sust@gmail.com

Huigang Liang
The University of Memphis, liangh@ecu.edu

Yajiong Xue
East Carolina University, xuey@ecu.edu

AI Aversion: A Task Dependent Multigroup Analysis

Short Paper

Md Jabir Rahman
The University of Memphis
Memphis, TN 38152
mrhman13@memphis.edu

Huigang Liang
The University of Memphis
Memphis, TN 38152
hliang1@memphis.edu

Yajiong Xue
East Carolina University
Greenville, NC 27858
xuey@ecu.edu

Abstract

Artificial Intelligence (AI) has been a subject of great interest for its potential to enhance human intelligence. However, existing findings suggest that user opinions about AI are mixed, with some embracing it while others express deep concern and try to avoid it. Here, we conducted a comprehensive review of relevant research to identify potential antecedents to AI aversion. Based on the theory of effective use and the adaptive structuration theory, we collapsed the precursors into four dimensions to develop a concise research model that holistically explains users' AI aversion. We then conducted online experiments to test the hypotheses empirically. The results indicate that perceived AI bias and perceived social influence are strong predictors of AI aversion. Additionally, a significant difference was found between the simple and complex task groups. These findings provide insights into the factors that contribute to AI aversion and have implications for designing and developing AI systems.

Keywords: Human-AI Interaction, AI Aversion, Multigroup SEM, AI Bias

Introduction

While an algorithm is a finite set of rules designed to solve a specific problem (Knuth, 1997), Artificial Intelligence (AI) is a very special type of algorithm that requires a special attention. According to existing literature, *AI is an information processing system that can interpret external data accurately, learn from it, and use the acquired knowledge to achieve specific goals or complete tasks through adaptation to its environment* (Haenlein & Kaplan, 2019). The potential of AI to improve human decision-making (Prahl & Van Swol, 2017) has led to significant attention and usage in various fields such as shopping recommendations (Amazon), autonomous vehicles (Tesla), healthcare (IBM Watson), Chatbots (EVA), Gaming (AlphaGo), among others. AI is highly desirable because it can automate tasks, outperform humans, reduce costs, and improve productivity. For instance, Netflix, the streaming giant, saves nearly a billion dollars annually by using an automated recommendation system (Gomez-Uribe & Hunt, 2015).

Although Artificial Intelligence (AI) has the potential to improve human lives and benefit society, literature suggests that people often exhibit aversion towards it (e.g., Fildes & Goodwin, 2007; Dietvorst et al., 2020; Prahl & Swol, 2017). For example, most Americans are found hesitant to accept driverless cars or robots as caregivers (Smith & Anderson, 2017). Likewise, Press (2019) found that 86% of consumers prefer interacting with humans over chatbots. According to the existing literature (Dietvorst et al., 2020; Jussupow et al., 2020), AI aversion is defined as "*the human assessment of an AI that manifests in a negative affective reaction with concomitant cognitions and behaviors towards it*." Given that consumer acceptance is vital to the success of any IT artifact, exploring AI aversion is crucial and valuable for businesses, particularly in the autonomous industry.

The existing literature on AI aversion primarily focus on surveying users' opinion based on a comparison between AI and human (e.g., Kießling et al. 2021) or investigating factors related to AI and user that lead to AI aversion (e.g., Lanz et al. 2023). Most studies in this area are scenario-based online survey or experiments in laboratory settings where users lack a true experience of using an AI (Mahmud et al., 2022). While factors related to AI and user are crucial, IS studies indicate that task characteristics (Castelo et al. 2019) and application environment (e.g., Prat et al. 2014) can significantly affect users' evaluations (e.g., Fang et al. 2005). Hence, a complete picture can only be drawn when we include the task and the environment along with AI and user in our research model. Moreover, literature on AI aversion presents conflicting findings. For instance, in response to Longoni et al. (2019), Pezzo and Beckstead (2020) argued that people prefer Artificial Intelligence (AI) over humans when it outperforms humans. Contrary to this, Dietvorst et al. (2020) demonstrated that people are less likely to use a model with better performance if it is unreliable and does not produce consistent results. Hence, it is evident that existing research lack a comprehensive research model as well as does not offer any reconciliation to the aforementioned conflict in findings. To address this research gap, we aim to develop a holistic research model guided by the following research questions: Why do people exhibit aversion towards AI, and does it vary based on the complexity of the task?

Through the lenses of the theory of effective use (TEU) and adaptive structuration theory (AST), we propose our research model that connect four possible dimensions of AI application and conduct an experimental study to test the model. Our data analysis reveals that several antecedents, such as perceived algorithmic bias and perceived social influence, positively impact users' AI aversion. Furthermore, we find that the strength of these relationships varies significantly between simple and complex tasks.

Our study makes significant theoretical and practical contributions. First, utilizing TEU and AST, we develop a research model for explaining users' AI aversion that fulfills the need for a concise research model. Second, we identify & empirically test potential factors responsible for AI aversion by synthesizing the literature on algorithm aversion, human-computer interaction, technology deterrence, and algorithm appreciation. Third, we conduct a task-dependent inter-group comparison experiment and analyze the results using structural equation modeling to investigate whether aversion varies based on the complexity of the task. Our findings shed light on the reasons behind users' AI aversion and how it changes according to the task context.

Theoretical Development

Theoretical Framework

We draw on the theory of effective use (TEU) (Burton-Jones & Grange, 2013) and adaptive structuration theory (AST) (DeSanctis & Poole, 1994) to inform the development of our theoretical framework. Both TEU and AST have been used in prior IS literature e.g., Pool et al. 2022 (data privacy concern); E-leadership & teleworking (Contreras et al. 2020). While we do not strictly follow the propositions of these theories, we rely on their logic and rationales to justify the critical dimensions and constructs that we have chosen, following the approach of Liang et al. (2015). Based on TEU, we propose that AI involves a user (or users), the AI itself, and the task that the AI is intended to perform (Burton-Jones & Straub, 2006). Although TEU posits that AI use is socially constructed, it does not directly consider environmental factors (Liang et al., 2015). To complement this, we adopt AST, which suggests that "the major sources of structure for groups as they interact with an advanced information technology are the technology itself, the tasks, and the organizational environment" (DeSanctis & Poole, 1994, p.128). Since AI is an advanced, intelligent IT artifact in the form of software or a combination of both software and hardware, we integrate TEU and AST and propose that users' AI aversion is shaped by factors that can be grouped into four categories: task characteristics, AI characteristics, user characteristics, and environmental characteristics (figure 1). Because it is impossible to consider all possible factors that might influence AI aversion in a single study, we select a representative construct in each category with strong theoretical and practical relevance. For example, from the environment dimension, while studies suggest other possible factors e.g., lack of incentivization, human in the loop (Burton et al. 2020), we select perceived social influence (PSI) for several reasons. First, IS literature on technology adoption & deterrence have put high emphasis on PSI because of its ability to shape users' opinions. For a comprehensive literature review, please check (Lorenz & Buhtz 2017; Graf-Vlachy & Buhtz 2017). Second, the number of different social media groups related to AI has increased tremendously in recent years. For example, searching with the keyword 'chatGPT' on Facebook by the author resulted in thousands of relevant groups. Moreover, the number of content creators in other medium (e.g., YouTube) has also been high. All these contribute to the availability of information that users consume every day and shape their opinions (e.g., Tresa Sebastian et al. 2021; Xiao et al. 2018). While other factors (e.g., an incentivized situation) relevant to environment are important, perceived social influence is much wider, generic and more applicable to understand AI aversion.

Figure 1 depicts our research model, which proposes that perceived AI bias (PAB), perceived social influence (PSI), and perceived lack of autonomy (PLA) positively impact AI aversion and that these relationships vary based on task complexity. To address alternative explanations, we control for age, education, and gender, commonly included in studies on technology adoption and algorithm aversion (Dietvorst et al., 2020).

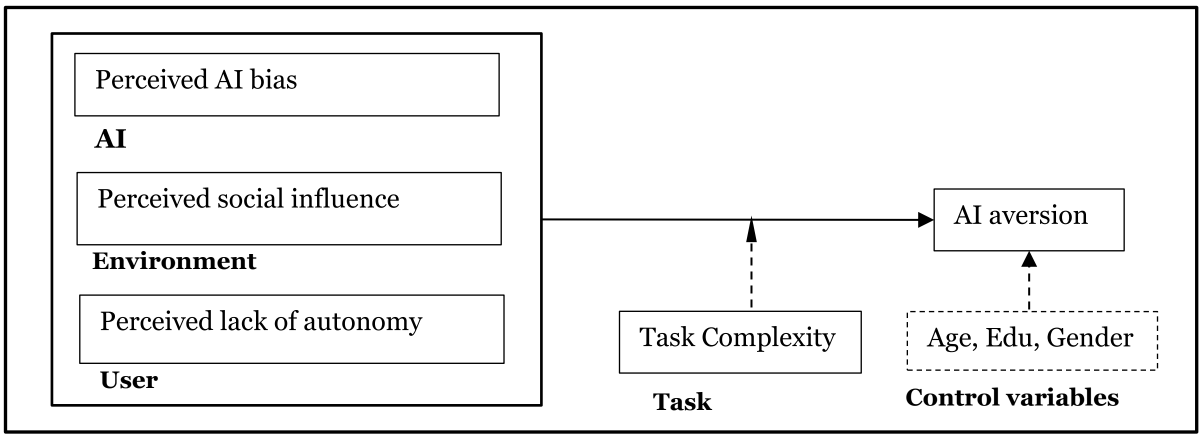

Figure 1. Research Model

Hypotheses Development

Perceived AI bias refers to a user's perception of an AI's potential to exacerbate existing inequalities in socioeconomic status, race, ethnicity, religion, gender, disability, or sexual orientation, thereby increasing inequalities in the applied field (Panch et al., 2019). Due to the profound social implications of algorithmic bias, recent studies on machine learning and AI have focused on the vulnerabilities of algorithms to bias. For instance, Lambrecht and Tucker (2019) found that an algorithm initially designed as gender-neutral exhibited discriminatory behavior. Since an AI's output depends on the quality of input data and the human-developed algorithms that govern its calculations, an AI may inherit biases from its developers. Previous research indicates that people are less confident in biased individuals (Yeung, 2019), and users tend to distrust biased recommendation systems (Chau et al., 2013). Therefore,

***H1**: Perceived AI bias is positively associated with AI aversion*

Perceived social influence is a construct that refers to the degree to which users perceive that people important to them believe they should perform a specific IT behavior (Venkatesh et al., 2003). In the context of our research, this specific IT behavior is AI aversion. Studies have found that social influence can be responsible for changing someone's thoughts, feelings, attitudes, or behaviors (Walker, 2007). Users can adjust their opinions or behaviors based on interactions with someone they consider necessary or an expert. Additionally, if a large portion of a user's social group holds a particular view, the user is more likely to accept that opinion (Walker, 2007). Social influence can occur directly (e.g., a direct opinion from a social group member to another regarding an AI) or indirectly (e.g., by offering an incentive). This is substantially critical in the context of AI aversion, as using augmented decision-making requires additional motivation.

Moreover, decision-making is an integral part of a social setting, and influential people in that social environment can expect others to conform to certain norms. Thus, perceived social influence has the potential to deter users from using AI. Hence, we propose,

***H2**: Perceived social influence is positively associated with AI aversion*

Perceived lack of autonomy refers to the degree to which users perceive no control over using an AI (Liang et al., 2015). Prior studies on technology acceptance and exploratory use have identified user autonomy as a crucial antecedent. If users believe they have little control over an AI, either in using it or selecting desirable features, their opinions may be negatively impacted (Burton et al., 2020). According to prior research, autonomy and independence are essential concerns regarding deploying robotic and autonomous systems in healthcare (Tan et al., 2021). Conversely, research has shown that users exhibit less aversion if they have the autonomy to modify an algorithm (Dietvorst et al., 2020). Therefore,

***H3**: Perceived lack of autonomy is positively associated with AI aversion*

Next, we propose that task complexity will moderate the effects of AI bias, social influence, and lack of autonomy on AI aversion. Task complexity refers to the attentional capacity or mental processing a user requires to complete a task (Bonner, 1994). It increases with the number of instructions or dimensions users must consider while performing a task. For example, people may perceive riding a bicycle as a simple task but flying a plane as a complex task. Established literature in different domains have proposed and studied task complexity as an important moderator (e.g., Wood et al. 1987; Almaatouq et al. 2021; Weiss-Cohen et al. 2018). Because increasing complexity increases the entropy of a task (Weiss-Cohen et al. 2018), complex tasks will require a higher level of skills and expertise. Hence, individual's perception, cognition, and emotional response to AI will differ based on their subjective interpretation of the level of complexity inherent in a task (Liu & Li, 2012).

For instance, despite their potential to mimic human-like intelligence, AIs are prone to bias, mainly when developed for complex tasks. AIs trained on a significantly higher number of factors for a complex task are more likely to accrue bias. Identifying the source of bias in such an AI is also more challenging. For example, Amazon developed an AI for employee recruitment, which turned out to be gender biased. Amazon could not identify the bias's root cause and had to terminate using the AI entirely (Dastin, 2018). From a user's perspective, the inability to identify the source of bias will exacerbate the situation, particularly for complex tasks, and result in a stronger aversion to AI. Hence,

***H4a**: The effect of perceived AI bias is higher for complex tasks than simple tasks*

Second, the influence of a user's social environment on their decision to use an AI may be less impactful for complex tasks compared to simple ones. This is because, for complex tasks, it can be difficult for people to agree on whether an AI should be used due to various factors that make individuals focus on different aspects of the application (Liu & Li, 2012). As a result, conflicting opinions within a user's social group may lead to confusion and uncertainty, reducing the social influence on the user's behavior. In contrast, for simple tasks, it is easier for people to reach a consensus on the application of AI, resulting in a more substantial and self-reinforcing social influence on the user's behavior (Walker, 2007).

***H4b**: The effect of perceived social influence is higher for simple tasks than for complex tasks*

Finally, the complexity of a task contributes to the uncertainty of its outcome, making it more difficult for users to predict the results (Schroder et al., 1967). Users want autonomy to control the outcome when working on complex tasks (Osman, 2010). The higher the uncertainty due to the complexity of the task, the more autonomy users would prefer. Thus, any AI agent threatening users' autonomy would face stronger aversion in complex task environments. On the other hand, users are more likely to delegate simple tasks to an AI agent due to the lower uncertainty in the outcome. For instance, Dietvorst et al. (2018) showed that in uncertain decisions, users are more likely to accept an AI if they can modify it, which gives them control over the AI's decision-making process. Hence,

***H4c**: The effect of perceived lack of autonomy is higher for complex tasks than simple tasks*

Methodology

Data Collection

To test our research model, we conducted online experiments using Amazon's Mechanical Turk, a widely used platform for online data collection (Paolacci et al., 2010). We assigned participants randomly to one of two groups and offered a freely available AI tool: a movie recommendation AI for the simple group and a health condition diagnosis AI for the complex group. Both tools are AI powered and clearly stated by respective developers. Participants were asked to use the AI tool, check its recommendations and complete a survey afterwards measuring the critical constructs in our research model. As indicated by Mahmud et al. (2022), majority of current studies on algorithm aversion employ online scenario surveys or laboratory experiments where users do not get a true experience. We wanted our participants to actively use the AI tools so they can have a higher engagement and more realistic responses. Many IS studies accepted a similar multi-method approach to gain a more comprehensive and richer understanding of a phenomenon (e.g., Cyr et al. 2009). A total of 398 responses were collected, with 83 responses rejected due to failing quality control questions embedded in the survey. The final dataset included 315 responses, 174 in the superficial group and 141 in the complex group. Our respondents were diverse in terms of gender (61% male, 39% female), age (ranging from 21 to 50+), and education level (ranging from high school to Ph.D.). We did not specify any other inclusion criteria, as we aimed to study the general perception and behavior of AI users. Participants were informed that the survey was anonymous, and that no personal information would be collected.

Measurement Development

The measurement instruments are adapted from validated measures and extant literature. PAB, PSI, & PLA are three items constructs and use a 7 points Likert scale. We measure task complexity using a single item following (Wang et al. 2014) to check the validity of task complexity manipulation. To rule out alternative explanations, we control for age, education, and gender (Dietvorst et al., 2020). The measures were initially tested on 100 undergraduate students, and their reliability and validity were checked. The student responses were not included in the final data set for analysis.

Results

The covariance-based structural equation modeling (CBSEM) tests the research model. We use IBM AMOS 27 for this purpose.

Measurement Model

We assessed the measurement model's reliability, convergent validity, and discriminant validity to evaluate the research model. The composite reliability and Cronbach's alpha for each construct were more outstanding than 0.7, indicating good construct reliability (Hair, 2009), as shown in Table 1 below. While all the items had loadings above 0.7, four were below 0.7 but above the acceptable threshold of 0.6 (Chin, 1998), indicating satisfactory convergent validity. We also examined discriminant validity by comparing the factor loadings on their construct with those on other constructs (Fornell & Larcker, 1981) and found satisfactory discriminant validity. We also conducted Harman's one-factor test to check for common method bias (CMV) and found that our data did not suffer from high CMV (Liang et al., 2015).

	Mean	CR	Alpha	SD	N	AB	LA	SI	AA	VIF
AB	4.00	0.85	0.9	1.78	315	1				2.142
LA	4.74	0.88	0.86	1.64	315	.44**	1			1.391
SI	3.69	0.80	0.94	1.95	315	.64**	.43**	1		3.03
AA	3.56	0.88	0.95	1.97	315	.75**	.43**	.78**	1	

Table 1: Statistics and correlations

Manipulation Check

We conduct a t-test to check if our manipulation of task complexity works. The result shows that the health condition diagnosis group has a significantly higher complexity score than the movie recommendation group ($p < 0.01$; $F = 42.033$, $df = 313$), indicating a successful manipulation.

Structural Model

We evaluated the hypotheses by analyzing the direction and significance of path coefficients in the SEM model, utilizing a bootstrapping procedure with 2000 resamples. Table 2 displays the results of our model testing. Our findings indicate that perceived AI bias and social influence positively relate to AI aversion. Interestingly, the relationship between perceived lack of autonomy and AI aversion is not significant. The control variables were also not significant. The SEM model demonstrated acceptable goodness-of-fit (Chi-squared/df = 1.81, CFI = 0.97, NFI = 0.95, and RMSEA = 0.051). These values surpass the recommended thresholds, indicating an excellent model-data fit (Suki, 2014; Hu & Bentler, 1999).

Variable	Full Sample	Simple Task	Complex Task
Algorithm Bias	0.51 (0.08)**	0.33 (0.11)**	0.83 (0.14)**
Social Influence	0.53 (0.07)**	0.57 (0.07)**	0.11 (0.15)
Lack of Autonomy	0.008 (0.08)	0.10 (0.12)	0.08 (0.12)
R^2	0.80	0.79	0.86

** p<0.01, * p<0.05. Standard errors are in parentheses.

Table 2: Results of Model Testing

Moderating Effect of Task Complexity

To test for differences in the strength of the structural relationships between simple and complex tasks, we conducted a multi-group analysis by using AMOS 27. First, we compared the unconstrained model with a competing model in which structural parameters were constrained to equality between the two task groups. The Chi-square test shows that the two models are significantly different (df = 11, CMIN = 33.13, $p < 0.05$), indicating significant differences in the relationships between the two task groups. We also checked for any significant difference between these groups for each hypothesized relationship individually. We found that perceived algorithmic bias is more substantial for complex tasks, while perceived social influence has a more substantial effect on simple tasks than complex tasks. Interestingly, perceived lack of autonomy is insignificant for any task group. In summary, H1, H2, H4a, and H4b are supported, but H3 or H4c are not.

Discussion

Implications for Research

Our study has several implications for research. First, we developed a concise framework that addresses all four dimensions of AI use: AI, user, environment, and task. This framework provides a comprehensive and systematic approach to studying the factors contributing to users' AI aversion behavior (Liang et al. 2015). Second, we identified essential factors related to these four domains by synthesizing literature from several disciplines. We reviewed relevant research on users' attitudes toward AI and analyzed the findings to explain why users may be averse to using AI in certain situations. Third, we empirically tested our model using an experiment. The results of our study provided strong support for our hypothesized model, indicating that the framework we developed accurately captures the factors that influence users' AI aversion behavior. Fourth, we considered task complexity a moderator and empirically validated its impact on users' attitudes towards AI. While current literature has rarely examined (except Castelo et al. 2019) task characteristics in the context of algorithm aversion, we found significant differences between simple and complex task groups. This highlights the importance of considering task complexity when studying and developing AI. Therefore, our study offers a comprehensive framework and empirical evidence to guide future research on users' attitudes toward AI. We have provided valuable insights into the factors influencing users' AI aversion behavior by considering all four dimensions of AI use, synthesizing existing literature, and empirically testing our model.

Implications for Practice

The findings of our study have practical implications for industries planning or implementing AI into their decision support systems. Firstly, these industries need to consider the possible negative aversion that users may have toward AI. To address this issue, enterprises are advised to take all possible measures, including leveraging social media platforms, to develop a positive perception of AI before introducing it on a large scale, especially for complex tasks. This recommendation is supported by extant research on word of mouth (Kozinets et al., 2010). Secondly, our study highlights the significant impact of perceived AI bias on AI aversion. Therefore, industries must ensure that the training data for their AI agent is free from discrimination. Developing an AI that is free from bias and capable of delivering accurate user results should be a top priority. Our study offers two practical implications for industries incorporating AI into their decision-making processes. First, they should take measures to develop a positive perception of AI among users, especially for complex tasks, through marketing efforts, including social media. Second, they should ensure that their AI agents are free from bias to reduce the potential negative aversion from users. These recommendations can help industries successfully implement AI into their operations and improve decision-making processes.

Limitations and Future Research

Several limitations to this study should be acknowledged. Firstly, our sample consists of respondents from the U.S. Therefore, the generalizability of our findings may be limited by cultural factors. While all participants had computer use experience, other factors may influence our results, such as access to AI tools or information. Future studies should explicitly consider established cultural factors in their research to address this. Secondly, our study is based on cross-sectional data, which cannot support claims for a causal relationship. While we randomized the task contexts, we did not manipulate the independent variables. Future studies should employ more robust randomized experiments to investigate how users' perceptions cause AI aversion. Thirdly, while we have selected essential factors from all four domains of AI application (i.e., AI, user, environment, and task), other potential factors could influence our findings. For instance, perceived user self-efficacy or task subjectivity could be important constructs that future studies consider including in their models. Fourthly, our study did not find a significant effect of users' perceived lack of autonomy on AI aversion. As mentioned, this could be due to our low-stakes tasks, and users may not be concerned about their autonomy. Future research could investigate this relationship in an experimental setting where the result of AI poses a higher threat to users. These limitations highlight the need for further research on the factors contributing to AI aversion and caution against overgeneralizing our findings.

Conclusion

This study contributes significantly to the IS literature by providing insights into the factors influencing users' AI aversion behavior. We provided a holistic understanding of the phenomenon by combining extant literature from various domains and developing a concise model that connects four possible dimensions of AI application: AI, task, environmental, and user characteristics. Our empirical findings support the direct effect of perceived AI bias and perceived social influence on AI aversion and demonstrate the importance of intergroup differences between simple and complex task groups in shaping these relationships. Despite some limitations, our study provides valuable insights that can guide future research and practical applications of AI. Our findings highlight the need for further research to understand better how users perceive and interact with AI, which can inform the development of more user-friendly and trustworthy AI systems.

References

Almaatouq, Abdullah, Mohammed Alsobay, Ming Yin, and Duncan J. Watts. "Task complexity moderates group synergy." Proceedings of the National Academy of Sciences 118, no. 36 (2021): e2101062118.

Bonner, S. E. (1994). A model of the effects of audit task complexity. Accounting, organizations and society, 19(3), 213-234.

Burton, J. W., Stein, M. K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. Journal of Behavioral Decision Making, 33(2), 220-239.
Burton-Jones, A., & Grange, C. (2013). From use to effective use: A representation theory perspective. Information systems research, 24(3), 632-658.
Burton-Jones, A., & Straub Jr, D. W. (2006). Reconceptualizing system usage: An approach and empirical test. Information systems research, 17(3), 228-246.
Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. Journal of Marketing Research, 56(5), 809-825.
Chau, P. Y., Ho, S. Y., Ho, K. K., & Yao, Y. (2013). Examining the effects of malfunctioning personalized services on online users' distrust and behaviors. Decision Support Systems, 56, 180-191.
Chin, W. W. (1998). The partial least squares approach to structural equation modeling. Modern methods for business research, 295(2), 295-336.
Contreras, F., Baykal, E., & Abid, G. (2020). E-leadership and teleworking in times of COVID-19 and beyond: What we know and where do we go. Frontiers in psychology, 11, 590271.
Cyr, D., Head, M., Larios, H., & Pan, B. (2009). Exploring human images in website design: A multi-method approach. MIS quarterly, 539-566.
DeSanctis, G., & Poole, M. S. (1994). Capturing the complexity in advanced technology use: Adaptive structuration theory. Organization science, 5(2), 121-147.
Dietvorst, B. J., & Bharti, S. (2020). People reject algorithms in uncertain decision domains because they have diminishing sensitivity to forecasting error. Psychological science, 31(10), 1302-1314.
Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. Management Science, 64(3), 1155-1170.
Dastin, J. (2018). Amazon scraps secret AI recruiting tool that showed bias against women. U.S. Retrieved August 27, 2022, from https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G
Fang, X., Chan, S., Brzezinski, J., & Xu, S. (2005). Moderating effects of task type on wireless technology acceptance. Journal of Management Information Systems, 22(3), 123-157.
Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of marketing research, 18(1), 39-50.
Fildes, R., & Goodwin, P. (2007). Against your better judgment? How organizations can improve their use of management judgment in forecasting. Interfaces, 37(6), 570-576.
Gomez-Uribe, C. A., & Hunt, N. (2015). The netflix recommender system: Algorithms, business value, and innovation. ACM Transactions on Management Information Systems (TMIS), 6(4), 1-19.
Graf-Vlachy, L., & Buhtz, K. (2017). Social influence in technology adoption research: a literature review and research Agenda. In Twenty-Fifth European Conference on Information Systems (ECIS), Guimarães, Portugal.
Hair, J. F. (2009). Multivariate data analysis.
Jussupow, E., Benbasat, I., & Heinzl, A. (2020). Why are we averse towards algorithms? A comprehensive literature review on algorithm aversion.
Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. California management review, 61(4), 5-14.
Kießling, S., Figl, K., & Remus, U. (2021). Human Experts or Artificial Intelligence? Algorithm Aversion in Fake News Detection.
Knuth, D. E. (1997). The art of computer programming (Vol. 3). Pearson Education.
Kozinets, R. V., De Valck, K., Wojnicki, A. C., & Wilner, S. J. (2010). Networked narratives: Understanding word-of-mouth marketing in online communities. Journal of marketing, 74(2), 71-89.
Tan, S. Y., Taeihagh, A., & Tripathi, A. (2021). Tensions and antagonistic interactions of risks and ethics of using robotics and autonomous systems in long-term care. Technological Forecasting and Social Change, 167, 120686.
Lambrecht, A., & Tucker, C. (2019). Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of STEM career ads. Management science, 65(7), 2966-2981.
Lanz, L., Briker, R., & Gerpott, F. H. (2023). Employees Adhere More to Unethical Instructions from Human Than AI Supervisors: Complementing Experimental Evidence with Machine Learning. Journal of Business Ethics, 1-22.
Lorenz, G. V., & Buhtz, K. (2017). Social influence in technology adoption research: a literature review and research agenda.

Liang, H., Peng, Z., Xue, Y., Guo, X., & Wang, N. (2015). Employees' exploration of complex systems: an integrative view. Journal of Management Information Systems, 32(1), 322-357.
Liu, P., & Li, Z. (2012). Task complexity: A review and conceptualization framework. International Journal of Industrial Ergonomics, 42(6), 553-568.
Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. Journal of Consumer Research, 46(4), 629-650.
Mahmud, H., Islam, A. N., Ahmed, S. I., & Smolander, K. (2022). What influences algorithmic decision-making? A systematic literature review on algorithm aversion. Technological Forecasting and Social Change, 175, 121390.
Osman, M. (2010). Controlling uncertainty: a review of human behavior in complex dynamic environments. Psychological bulletin, 136(1), 65.
Panch, T., Mattie, H., & Celi, L. A. (2019). The "inconvenient truth" about AI in healthcare. NPJ digital medicine, 2(1), 1-3.
Paolacci, G., Chandler, J., & Ipeirotis, P. G. (2010). Running experiments on amazon mechanical turk. Judgment and Decision making, 5(5), 411-419.
Pezzo, M. V., & Beckstead, J. W. (2020). Algorithm aversion is too often presented as though it were non-compensatory: A reply to Longoni et al.(2020). Judgment and Decision Making, 15(3), 449.
Pool, J., Akhlaghpour, S., Fatehi, F., & Gray, L. C. (2022). Data privacy concerns and use of telehealth in the aged care context: An integrative review and research agenda. International Journal of Medical Informatics, 104707.
Prahl, A., & Van Swol, L. (2017). Understanding algorithm aversion: When is advice from automation discounted?. Journal of Forecasting, 36(6), 691-702.
Prat, N., Comyn-Wattiau, I., & Akoka, J. (2014). Artifact evaluation in information systems design-science research–a holistic view.
Press, G. (2019, October 2). AI Stats News: 86% Of Consumers Prefer Humans To Chatbots. Forbes.com. Retrieved May 27, 2023, from https://www.forbes.com/sites/gilpress/2019/10/02/ai-stats-news-86-of-consumers-prefer-to-interact-with-a-human-agent-rather-than-a-chatbot/?sh=68ea03cd2d3b
Schroder, H. M., Driver, M. J., & Streufert, S. (1967). Human information processing: Individuals and groups functioning in complex social situations. Holt, Rinehart and Winston.
Smith, A., & Anderson, M. (2017). Automation in everyday life.
Tresa Sebastian, A., Lal, B., Anupama, J., Varghese, J., Agnus Tom, A., Rajkumar, E., ... & John, R. (2021). Exploring the opinions of the YouTube visitors towards advertisements and its influence on purchase intention among viewers. Cogent Business & Management, 8(1), 1876545.
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS quarterly, 425-478.
Walker, L. S. (2007). Social influence. The Blackwell encyclopedia of sociology.
Wang, Q., Yang, S., Liu, M., Cao, Z., & Ma, Q. (2014). An eye-tracking study of website complexity from cognitive load perspective. Decision support systems, 62, 1-10.
Weiss-Cohen, L., Konstantinidis, E., Speekenbrink, M., & Harvey, N. (2018). Task complexity moderates the influence of descriptions in decisions from experience. Cognition, 170, 209-227.
Wood, R. E., Mento, A. J., & Locke, E. A. (1987). Task complexity as a moderator of goal effects: A meta-analysis. Journal of applied psychology, 72(3), 416.
Xiao, M., Wang, R., & Chan-Olmsted, S. (2018). Factors affecting YouTube influencer marketing credibility: a heuristic-systematic model. Journal of media business studies, 15(3), 188-213.
Yeung, L. L. (2019). Bias, insecurity and the level of trust in the judiciary: the case of Brazil. Journal of Institutional Economics, 15(1), 163-188.