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Understanding Resistance to Organizational AI Adoption

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Roundtable: Artificial Intelligence

Abstract

The purpose of this mixed-method case study was to understand why employees within an organization are hesitant to adopt large language models, demonstrate that quantitative scales can be used imperfectly to identify issues, and artificial intelligence (AI) can quickly help leaders understand these results and their associated risks and biases. When utilized ethically, AI can enhance organizational efficiency and support human flourishing (Spitko, 2024; Stahl et al., 2021). The two most common ways AI is employed within an organization are automating routine tasks and augmenting decision making (Bankins et al., 2024; Kulat & Pais, 2024). However, the introduction of AI within an organization often encounters stiff resistance (McCall, 2025; Weber et al., 2023). Therefore, this study used Armenakis et al.'s (2007) Organizational Change Recipients' Belief Scale (OCRBS) to assess employees' belief structures underlying their resistance and to identify the primary driver quickly. The OCRBS was administered to the organization's six-person administrative department and measured five dimensions: discrepancy, appropriateness, efficacy, principal support, and valence. After the primary resistance driver of the discrepancy was identified, focused qualitative data were collected to confirm and better understand this finding. AI was also used to augment decision making by gaining a deeper understanding of any risks, biases, and ambiguous scale results. The results of this study contribute to existing theory by demonstrating the applicability of the OCRBS to understand resistance to AI; imperfectly applying scales to help identify change resistance; and the use of AI by practitioners and academics to augment decision making and explore challenges and issues.

Keywords: artificial intelligence, leadership, change management

If you were to search Google Scholar for a combination of artificial intelligence (AI), machine learning, and human flourishing, the result would be in the thousands. While not every article or journal would apply, the returned scholarly articles and journals

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would largely conclude that AI supports human flourishing by augmenting decision making and automating routine tasks (Miller, 2022; Stahl, 2021; Zhao & Sun, 2025). For example, augmenting decision making, especially in healthcare, promotes human flourishing by identifying health issues more rapidly and accurately and by providing a more tailored medical or healthcare plan (Esteva et al., 2019; Miotto et al., 2018). Automation supports human flourishing by giving individuals time back to focus on more strategic and complex tasks or pursue personal interests (Abasaheb & Subashini, 2023). Since time is our most valuable resource, providing more time to an individual is one of the most significant ways AI enables human flourishing. However, most often, the adoption of AI within an organization is met with resistance.

The resistance to adopting AI was experienced firsthand when an administrative department resisted and ultimately rejected the use of a Chatbot to generate routine administrative documents. The administrative department consists of six individuals responsible for processing thousands of routine pieces of correspondence each year. To alleviate bottlenecks and recapture man-hours, leadership decided to implement a Chatbot. The Chatbot would automate a large majority of the annual correspondence and generate documents ready for routing and signature in Microsoft Word. However, as in other studies (Ivchyk, 2024), during the rollout phase, the Chatbot encountered significant individual behavioral resistance, leading to its rejection. The rejection confused leadership, as leadership viewed it to reduce individual burden and capture efficiencies in routine processes.

Given these challenges and the phenomenon's firsthand experience, this exploratory case study sought to accomplish two goals. First, it aimed to help leaders successfully navigate change resulting from the introduction of AI, specifically large language models, within their organizations. Next, it demonstrated that leaders can utilize AI to augment their decision making when faced with minimal information. This exploratory mixed-method case study achieved this through quantitative analysis supported by qualitative data to understand the primary behavioral resistance to adopting a Chatbot powered by a large language model within an organization. The Chatbot was designed to automate routine correspondence within the study's organization's administrative department, saving valuable time and resources. However, its adoption was rejected. Due to the small sample size of six, these results are neither definitive nor should they be used. Instead, the results are presented to stimulate further exploration of this phenomenon and to demonstrate how organizational leaders may imperfectly apply validated scales and quantitative methods, augmented with AI, to save time and resources by quickly identifying the primary behavioral resistance to change.

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Literature Review

Technology plays a significant role in an organization's ability to gain a competitive advantage (Porter, 1985). While it plays such an important role, it also impacts an organization in two distinct ways—through its product or its processes (Porter, 1985). While AI affects both areas, this study focuses on its impact on an organization's processes. Primarily, AI affects an organization's processes in two ways: automation (Abasaheb & Subashini, 2023; Daradkah et al., 2024) and augmentation (Akyazi, 2023; Shah, 2024). Both impacts require change, which is one of the most challenging roles a leader will face (Yukl & Gardner, 2020).

R1: Can AI augment decision making to assist a leader in imperfectly applying a scale to identify the most significant change-resistant behavior?

Artificial Intelligence

Although AI has existed since the 1950s, it lacks a singular definitive definition (Enholm et al., 2022). For clarity, AI is defined in this exploratory case study as a nonbiological entity that possesses human-like capabilities, specifically reasoning, problem solving, and an understanding of its external environment based on the input it has received (Enholm et al., 2022; Eriksson et al., 2020; Mikalef & Gupta, 2021). There are three types of AI—narrow, general, and superintelligence (Tegmark, 2017). The predominant types of AI technology used in contemporary organizations are machine learning, natural language processing, computer vision, expert systems, planning and scheduling, and speech synthesis (Frank, 2024). The technology used in the current case study was a large language model, which originated from natural language processing.

Natural language processing blends AI and linguistics to enable computers to understand the words within the human language (Jarrahi, 2018). Natural language processing uses computational techniques and algorithmic structures to generate text based on word co-occurrence within a dataset (Chowdhary, 2020). Typical uses of natural language processing include categorization, machine translation, spam filtering, and summarization (Khurana et al., 2023). While natural language processing technology formulates responses using only data from a specific dataset (Chowdhary, 2020), large language models use deep neural networks to generate responses based on contextual information and learned behaviors (Idan & Einav, 2025). Because of this ability, today's Chatbots are powered by large language models. Although Chatbots are widely used and have transformed the way machines and humans interact, the change required to adopt them within an organization often meets substantial resistance (Ivchyk, 2024).

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Organizational Change

Lewin (1951) posited that organizational change comprised three steps—unfreezing, moving, and refreezing. Unfreezing refers to disrupting the current behaviors within an organization. Once disrupted and destabilized, the second step of moving can begin. In the second step, leaders motivate and encourage employees to learn new behaviors needed to support the change. Once learned, the final stage of freezing occurs. During this stage, the newly learned behaviors become the norm (Lewin, 1951).

When navigating change, a leader will often encounter resistance. There are two types of resistance—organizational and individual (Konopaske et al., 2018). Konopaske et al. (2018) concluded that organizational resistance includes structural inertia, perceived threats to the existing power balance, and organizational memory. At the individual level, resistance to change consists of behavioral, cognitive, and affective dimensions (Konopaske et al., 2018). While each dimension contributes to an individual's overall level of resistance, this exploratory mixed-methods case study focused only on the behavioral dimension. The behavioral dimension of change refers to an individual's physical actions or mental processes (Matlin, 1995). The Organizational Change Recipients' Belief Scale (OCRBS) is a validated instrument used by researchers to help determine which individual behavioral reaction is the primary driver in their resistance to change.

Organizational Change Recipients' Belief Scale

In the OCRBS developed by Armenakis et al. (2007), the authors posited that an individual's beliefs drive resistance. Therefore, the scale serves as a validated instrument for measuring individual beliefs that influence openness to change. The scale consists of five key individual dimensions—discrepancy, appropriateness, efficacy, principal support, and personal valence. Discrepancy is defined as an individual's belief that a change is needed or a sense of urgency for the change (Armenakis et al., 2007). Appropriateness is defined as the individual's belief that the identified change resolves the current issue or challenge (Armenakis et al., 2007). Next, efficacy refers to the individual's perceived ability and capability needed for the change (Armenakis et al., 2007). The dimension of principal support refers to leadership's support for the change. Finally, personal valence refers to the attractiveness of the change's benefit or what is in it for me.

The use of these five dimensions provides a comprehensive understanding of how an individual perceives and will respond to change. While not explicitly used to understand change resistance to the adoption of AI, the scale is commonly used in organizational change research. Fatima et al. (2022) also concluded that valence is commonly the primary driver of change. Therefore, leadership selected the scale for this

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case study to save time and minimize current operations by quickly confirming valence was the primary driver or identifying the primary behavioral driver that led to not adopting the Chatbot.

H_1: Valence is the primary behavioral dimension that causes the Chatbot to be rejected.

H_0: Valence is not the primary behavioral dimension that causes the Chatbot to be rejected.

Methodology

This exploratory case study used a mixed-method approach. A mixed-methods approach was used to help leadership save valuable time and reduce operational impact. The study organization's administrative department consists of six personnel; therefore, the sample size for this study was six. The small sample size poses a threat to the study's findings. These threats include generalizability, multicollinearity, reduced statistical power, reduced precision and reliability, and increased random variation. Given these challenges, the results of this case study are exploratory and should be used only to stimulate discussion and inform future research into this phenomenon. The independent variables used in this case study were discrepancy, appropriateness, efficacy, principal support, and personal valence. The dependent variable was resistance.

Quantitative data were collected using the OCRBS. This is a Likert-scale questionnaire with 20 questions, with 1 indicating the individual *strongly disagreed* and 6 indicating they *strongly agreed*. Qualitative data were collected after completion of quantitative analysis. Once the primary driver of change was identified, a focused, in-depth interview was conducted to validate the finding and understand the individual's perception that supported their resistance.

In the spirit of using AI to enhance decision making, analysis was conducted using ChatGPT. OpenAI (2025) stated that ChatGPT uses Python and leverages Panda and NumPy, as well as custom functions, to produce results that are statistically equivalent to those of SPSS. The analysis conducted using ChatGPT included descriptive, reliability, and regression. Due to the small sample size and associated threats, ChatGPT was used to explore the quantitative results further and gain a deeper understanding of the risks and threats posed by the small sample size. Confirmatory factor analysis was not completed due to the small sample size.

Bias may exist in the study due to two primary concerns. First, the researcher was the organization's leader. Next, the participants were within the organization in which the researcher was a part.

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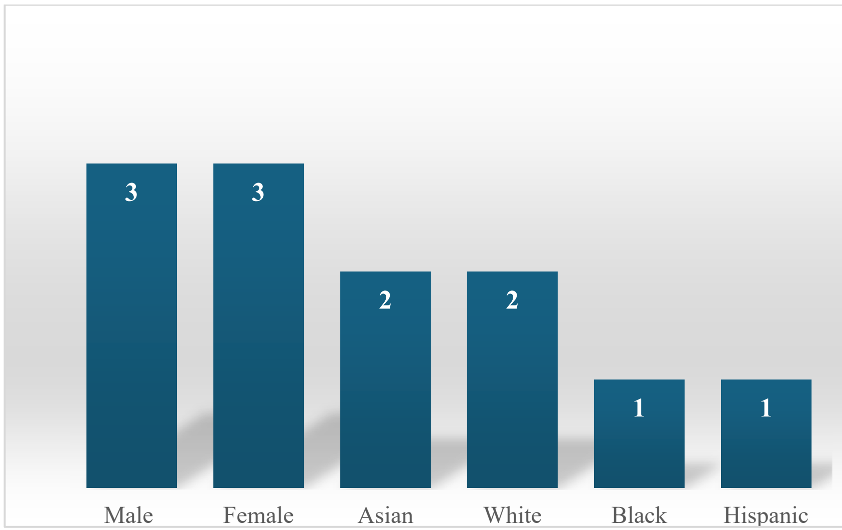
Data Analysis

The data collected from the study's participants reflected a diverse population (see Figure 1).

Figure 1: Participant Demographics



Descriptive Results

Table 1 indicates that the dimension of discrepancy possessed the lowest mean. This result suggested that although there existed a general readiness to adopt AI within the organization, the case study participants perceived a limited need to do so. It must again be emphasized that, although the results align with theoretical expectations, they are exploratory due to the small sample size. The small sample size makes it possible for an outlier to significantly affect the mean.

Table 1: Descriptive Analysis

Subscale	*N*	*M*	*SD*
DIS (Discrepancy)	6	3.50	1.04
APP (Appropriateness)	6	4.29	0.62
EFF (Efficacy)	6	4.46	0.43
PS (Principal Support)	6	4.54	0.53
PV (Personal Valence)	6	4.54	0.56

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Reliability Results

All subscales of the OCRBS were reliable, with scores above the normally accepted level of .70 (Nunnally, 1978). These results indicated that differences in the scores reflect genuine differences in beliefs rather than random noise. Thus, the conclusions are based on a valid and dependable scale rather than measurement error.

Table 2: Cronbach Alpha Results

Subscale	Items	α
DIS	4	.82
APP	4	.88
EFF	4	.84
PS	4	.86
PV	4	.91

Regression

First and foremost, regression analysis results should be used only to understand or visualize the direction and magnitude of a variable. Inferential tests are unreliable due to model saturation and multicollinearity. Furthermore, the variance inflation factor results indicated substantial multicollinearity, driven by the small sample size and high correlations among the predictors. R^2 was equal to 1.00 due to the small sample size of $n = 6$, indicating that coefficients should be interpreted descriptively instead of inferentially. The F statistic and p values are not meaningful with this n/p ratio.

However, the regression indicates that the discrepancy was the primary driver, as it had the largest absolute value. When viewing Figure 2, the resistance scale was reversed. Initially, resistance was coded so that higher values indicated less resistance. To align resistance with the OCRBS, the resistance items were reverse-scored so the regression coefficients could be interpreted correctly. The darker shade indicates that a higher belief results in lower resistance. In contrast, the lighter shade indicates that greater belief corresponds to greater resistance. In this instance, efficacy did not align with existing theory, which can be attributed to sampling variation caused by the small sample size.

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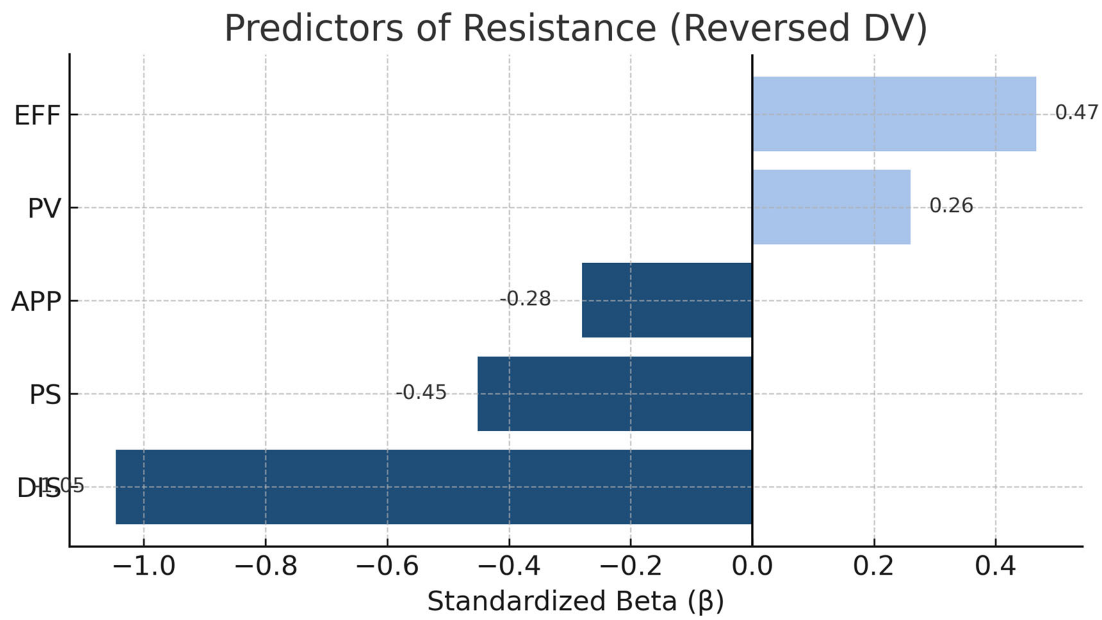
Figure 2: Regression Analysis



Although inferential tests are unreliable due to model saturation and multicollinearity, the researcher was able to quickly identify a primary belief driver. Once identified, ChatGPT was used to further explore this phenomenon. While further exploring, it must be noted that a researcher must have a working knowledge of statistics, as ChatGPT provided incorrect answers. These answers were largely contributed to rounding errors and improper prompting. However, a working knowledge can identify these challenges and readdress them through improved prompts. Once understood, questions were developed to validate that the primary belief was in discrepancy and to understand why individuals did not perceive the need for change.

Qualitative Results

Qualitative data analysis focused on validating the regression findings and understanding the individual's perception of not needing to change. From these questions, two themes emerged. The first was that the individuals did not perceive a need for change. This finding validates the regression result that discrepancy was the primary belief driving resistance to change. Next, the individuals did not perceive the need to change as they viewed their current process of manually generating and correcting routine correspondence as adequate.

Discussion

Research Question 1 asked, can AI augment decision making to assist a leader in imperfectly applying a scale to identify the most significant change-resistant behavior?

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This exploratory case study demonstrated that it is plausible for a leader to use AI to utilize a validated instrument and to conduct quantitative analysis imperfectly.

An organizational leader faces many challenges and must often make informed, risk-based decisions. In this exploratory case study, the leader sought to adopt AI within the organization to capture efficiencies and alleviate bottlenecks downstream of the administration department. Upon rejection, the leader faced the decision to halt the administrative workflow to conduct an in-depth qualitative analysis or to use other means to minimize workflow disruption while still exploring why the adoption of AI was rejected. While the risk of stopping the administrative workflow for an extended period was too significant to accept, the risk to the workflow from imperfectly using a scale and quantitative analysis supported by AI is much lower. The administration and collection of quantitative data for the OCRBS were completed in less than 30 minutes, which is nominally shorter than the typical time for in-depth qualitative data collection. While the challenges posed by such a small sample size were well understood, quantitative data analysis enabled leadership to quickly identify that the discrepancy was the primary driver of participants' resistance to change.

This finding aligns with and is supported by previous studies (Bowen et al., 2017; Draucker et al., 2020; Hastings, 2022; Olivier, 2017). These authors concluded that mixed-method approaches provided practitioners with a quick and efficient means to identify problem areas. Specifically, the scales were used for pattern detection (Olivier, 2017), as a triage tool (Bowen et al., 2017), and to guide targeted qualitative questioning (Draucker et al., 2020; Hastings, 2022). Once quantitative data analysis was completed, Bowen et al. (2017), Draucker et al. (2020), Hastings (2022), and Olivier (2017) all concluded that follow-on qualitative analysis was required and enabled deeper exploration and understanding of the issue. Furthermore, the utility results of the OCRBS used in this study align with previous research (Burgan, 2014). Burgan (2014) used the OCRBS in a mixed-method project management adoption case study and concluded that the scale is an effective means to quickly isolate a problem, while follow-up interviews provided clarity on why the scores were low.

The use of ChatGPT also enhanced the leadership's understanding and comprehension of the issue. The incorporation of ChatGPT enabled leadership to delve deeper into the results, allowing them to fully understand the risks associated with a small sample size and its impact on statistical results. The use of ChatGPT also enabled those unfamiliar with statistics to gain a better understanding of the context and the second- and third-order impacts of the results, allowing them to query and challenge each result throughout the process. For example, the use of ChatGPT highlighted that the results of quantitative analysis should not be viewed as statistically significant or inferential. Instead, these results should only be used to understand the direction and magnitude of each dimension and its influence on change resistance. However, it must be noted that

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ChatGPT also made errors. A lack of a basic understanding of quantitative research will confuse leaders and researchers, leading to incorrect decisions.

Next, with the results of data analysis and an understanding of the area and severity of risk, leadership was able to quickly validate imperfect quantitative results through focused follow-on qualitative data collection. Through a focused follow-on qualitative data collection process, the stoppage of the administrative department's workflow was minimized, and risk was reduced to acceptable levels. Furthermore, it enabled leaders to quickly apply the minimum amount of excess resources against the problem. Ultimately, this preserved the most valuable resource—time.

These findings build upon previous research (Seoni et al., 2023; Steyvers & Kumar, 2024; Taylor et al., 2025; Wang et al., 2025). These authors concluded that practitioners can successfully incorporate AI into their decision making when used to help identify emerging risks (Taylor et al., 2025), bias (Wang et al., 2025), probability patterns (Steyvers & Kumar, 2024), and explore incomplete or ambiguous scale results (Seoni et al., 2023).

This exploratory case study also rejected its hypothesis. Building on previous research, this study hypothesized that valence was the main behavioral factor influencing the Chatbot's rejection. However, the findings of this case study showed that discrepancy was the key dimension predicting rejection. Due to the challenges and risks associated with quantitative analysis, this result was further examined through qualitative methods. Focused interviews helped the researcher validate this conclusion. Additionally, all participants indicated that adopting AI was exciting and that they were eager to do so. However, when asked about the Chatbot's purpose and intent, they expressed that they did not see the need for change and considered it unnecessary. From this, it is reasonable to conclude that if a person does not perceive a need for change, it is unlikely to happen regardless of other factors. While unexpected, the finding that, regardless of all other variables, an individual must first perceive the need for the change was demonstrated in previous research. In research about this phenomenon, Rafferty et al. (2013) and Weiner (2020) concluded that without a perceived need for change, organizational change readiness collapses and change implementation fails. Simply stated, no perceived need equates to no actual change (Weiner, 2020).

Similar to previous research by Banerjee and Lowalekar (2021), this is an important finding because it suggests that leaders should craft their communication to explain why adopting AI addresses an organizational problem, rather than a departmental or individual one. For instance, while staff within the administrative department felt the change was unnecessary, they were unaware of the downstream bottleneck their manual processes was creating. Specifically, the administrative team manually drafts

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documents or manually updates received documentation. These manual inputs often introduce errors, leading to rejected documents that must be returned to the originator. This rework causes delays and slows down other administrative tasks and correspondence. To overcome this challenge, leaders can shape their messaging using a systems engineering approach. As Banerjee and Lowalekar demonstrated, a systems engineering approach to change highlights the interconnectedness and interdependencies among individuals and processes within an organization. Thus, communicating at the organizational level will increase understanding and, therefore, reduce resistance by decreasing the discrepancy behavior dimension.

Conclusion

This exploratory case study had four significant implications. First, this case study demonstrated the utility of using Armenakis et al.'s (2007) OCBRS in navigating artificial adoption within an organization. Second, it showed that, regardless of other behavioral dimensions, if an individual does not perceive a need for change, the change is unlikely to occur. Third, to reduce discrepancy-based resistance to change, leaders should communicate the need for change and its benefits at the organizational level or through a systems approach. This will improve communication by highlighting and drawing attention to the true purpose of the idea (Adu-Oppong & Agyin-Birikorang, 2014) and showing the interdependence throughout the organization (Banerjee & Lowalekar, 2021). Finally, by augmenting decision making with AI, practitioners can imperfectly apply academic quantitative research methods to identify problems and quickly reduce their overall risk.

Future Research

Given the small sample size in this exploratory case study, future research should use a larger sample. As discussed, because of the small sample size, these results cannot be generalized to the broader population. Therefore, a larger sample will help validate and extend this study's findings. Additionally, this study was cross-sectional, so future research should use longitudinal methods to better understand resistance to adopting AI within organizations.

About the Author

Dominic Frank is a Commander in the U.S. Navy with over 30 years of service. He earned a Bachelor of Arts in Business Administration from Saint Leo University, an MBA from Texas A&M-Commerce, and a Ph.D. in Organizational Leadership from Regent University. Correspondence concerning this article should be addressed to dominic.r.frank@gmail.com.

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