

Artificial Intelligence-Based Communication and Work Performance: A Quantitative Case Study of a National Electricity Distribution Utility

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ABSTRACT

This study examines the relationship between Artificial Intelligence (AI)-based communication and employees' work performance, using a quantitative case study of the Utility Distribution Network (UDN). As AI increasingly mediates organizational communication through chatbots, dashboards, and automated alerts, understanding how it relates to employee-level outcomes has become critical, particularly in safety-critical infrastructure settings. Guided by Media Richness Theory, this study conceptualizes AI-based communication through six dimensions: information exchange, message reception, message understanding and feedback, message acceptance, persuasion, and reaction provocation. A cross-sectional survey was administered to 180 UDN executives who regularly interact with AI-based communication systems, and data were analyzed using descriptive statistics, Pearson correlation, and multiple regression. All six communication dimensions correlated positively with work performance; however, regression results indicated that only information exchange, persuasion, and reaction provocation were significant unique predictors of performance, with persuasion emerging as the strongest predictor. Findings suggest that AI-based communication is associated with higher work performance mainly where it clarifies information, influences behavior, and triggers timely action, rather than where it only delivers messages. Because the design is cross-sectional and limited to one organization, these associations should not be read as causal. The study applies Media Richness Theory to AI-mediated environments and offers preliminary practical guidance for designing AI communication systems in safety-critical organizations.

Keywords: Artificial intelligence communication; work performance; Media Richness Theory; quantitative case study; organizational communication; electricity distribution utility

INTRODUCTION

Organizational coordination, communication, and work performance have undergone significant change over the past decade as a result of rapid advances in digital technology. Among these advances, Artificial Intelligence (AI) stands out as a transformative driver within contemporary organizations (Hall et al., 2025). As AI becomes increasingly embedded in operational systems, it reshapes how knowledge workers gather, analyze, and respond to real-time information. AI is no longer confined to back-end analytical processing; it increasingly mediates workplace communication by generating alerts, summarizing operational risks, and recommending actions. This shift makes it essential to examine AI-based communication within operational environments to understand how it relates to employees' work performance and behavioral responses (Florea & Croitoru, 2025).

Electricity distribution utilities are a particularly relevant setting in which to examine this question. As

national utilities accelerate digital transformation driven by grid-modernization and energy-transition agendas, digital systems increasingly function as enablers of operational resilience and service continuity. The organization examined in this study, a distribution network division of a national electricity utility (UDN), has deployed a range of AI-driven tools, including predictive asset-analytics platforms, an advanced distribution management system, a smart-metering operations platform, and an AI-based chatbot. These tools generate continuous streams of system-based communication, such as predictive maintenance alerts, automated outage notifications, performance dashboards, and interactive support. Rather than operating independently of employees, these systems rely on human interpretation and response (Florea & Croitoru, 2025): engineers, technicians, and managers must receive, understand, and act upon AI-generated messages to ensure timely fault resolution, cost-optimized operations, coordinated maintenance, and operational safety.

The presence of intelligent systems, however, does not automatically translate into improved outcomes (Choung et al., 2025). AI contributes to performance only when employees trust, interpret, and integrate system-generated insights into their decision-making, and communication quality remains critical (Chen & Zhang, 2025). If AI-generated messages are unclear, excessive, or poorly prioritized, employees may experience cognitive strain or skepticism that weakens responsiveness and coordination. Conversely, when AI-based communication enhances information processing and message delivery, it can improve employee performance through greater clarity, timeliness, and responsiveness, tailoring messages to individual needs and reducing the time required to comprehend and act on them (Florea & Croitoru, 2025).

Drawing on Media Richness Theory (MRT), this study conceptualizes AI-based communication across six dimensions (information exchange, message reception, message understanding and feedback, message acceptance, persuasion, and reaction provocation), which are treated as communication processes that may be associated with work performance. Despite UDN's extensive digitalization, internal organizational evaluations have largely focused on system capability and macro-level digitalization progress rather than on how specific communication mechanisms relate to individual employees' task execution and behavioral responsiveness. Much of the broader AI literature similarly emphasizes adoption, strategic value, or organization-level productivity, leaving employee-level outcomes comparatively under-examined (Florea & Croitoru, 2025). This gap motivates the present study, a quantitative case study of UDN executives. Its objective is to examine whether information exchange, message reception, message understanding and feedback, message acceptance, persuasion, and reaction provocation are associated with work performance in UDN.

Theoretically, the study seeks to extend Media Richness Theory into AI-based communication environments by treating intelligent systems as active communication agents rather than passive channels, and by examining which communication dimensions are most strongly associated with performance in AI-mediated settings. Empirically, it addresses the limited evidence on how AI-based communication relates to individual-level performance in safety-critical utility settings, complementing a literature that has emphasized organization-level productivity and adoption outcomes. Practically, the findings offer preliminary, evidence-based guidance for prioritizing improvements in AI communication design, such as dashboard configuration, alert structuring, and chatbot interaction design, in organizations where communication failures carry operational and safety consequences. The remainder of this article is organized as follows: Section 2 presents the literature review and hypothesis development, Section 3 describes the methodology, Section 4 reports the results, and Sections 5 and 6 present the discussion, implications, and conclusions.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Media Richness Theory

Media Richness Theory (MRT), developed by Daft and Lengel (1986), proposes that communication effectiveness depends on a medium's capacity to convey rich information, immediate feedback, multiple cues, natural language variety, and personal focus. Lean media, by contrast, provide limited cues and delayed feedback. MRT further holds that highly equivocal (ambiguous) tasks require richer media to build

shared understanding, whereas routine tasks can be managed through leaner channels. In digitally enabled organizations, AI systems can simulate feedback immediacy and contextual interpretation (Bauer et al., 2025): dashboards provide real-time indicators, chatbots offer instant clarification, and predictive systems deliver proactive alerts. These features may increase the richness of digital communication beyond what traditional written channels offer, providing a relevant theoretical lens for examining whether AI-based communication is associated with employee work performance.

Applying MRT to AI-based communication suggests that AI tools can enhance the richness of digital communication by simulating key characteristics of rich media, such as feedback immediacy, ambiguity reduction, contextual responsiveness, and proactive information delivery (Chugh et al., 2025). AI chatbots minimize delays in clarification; real-time dashboards standardize data presentation and limit interpretive variance; automated decision-support mechanisms tailor recommendations to situational needs; and predictive alerts proactively flag issues before they escalate. When the richness of AI-based communication matches the complexity and equivocality of the task at hand, employees are better positioned to interpret information accu-

ately, respond promptly, and coordinate with stakeholders (Chen & Zhang, 2025), which in turn can reduce time, cost, and conflict arising from miscommunication.

Work Performance

Work performance refers to behaviors and outcomes that contribute directly to organizational goals, and is typically conceptualized as encompassing task, contextual, and adaptive performance (Johnson, 2001). This study focuses on individual-level task performance, operationalized through three measurable indicators: reduction in time, reduction in cost, and reduction in conflict. Unlike macro-level indicators such as organizational profitability, individual-level performance captures tangible improvements in employees' daily work outputs (Dalal et al., 2020). In digitally mediated environments, the clarity, responsiveness, and accuracy of information exchange become critical determinants of this performance, as effective communication reduces duplication of effort, shortens decision cycles, and minimizes friction among team members (Lane et al., 2024).

AI-Based Communication and Its Dimensions

AI-based communication refers to the deployment of AI systems to structure, prioritize, and enhance organizational information exchange (Hassan, 2024). Unlike traditional digital media that passively transmit messages, AI-enabled systems actively process data, generate insights, and facilitate interactive feedback. From an MRT perspective, AI-based communication represents an evolution of digital media capable of increasing richness through feedback immediacy, structured cue presentation, contextual interpretation, and personalized guidance (Kahai & Cooper, 2003). This study operationalizes AI-based communication through six dimensions. The rationale for selecting these dimensions is explained first, and each dimension is then defined.

The six dimensions were selected because, taken together, they follow the sequence through which an organizational message becomes work-relevant action. A message is first supplied (information exchange), then reaches its recipient (message reception), is interpreted and clarified (message understanding and feedback), is judged credible and accepted (message acceptance), influences the recipient's decisions (persuasion), and finally prompts a behavioral response (reaction provocation). This staged view of communication follows the six-dimension framework operationalized by Florea and Croitoru (2025), whose measurement items the present study adopts. Using an established set of dimensions, rather than constructing a new one, also allows the findings from this utility setting to be compared with those of the earlier study, which was conducted in a food-industry company.

The dimensions also correspond to the features that MRT treats as determinants of medium richness. Information exchange reflects the capacity to carry structured and multiple cues; message understanding and feedback and reaction provocation reflect feedback immediacy and the reduction of equivocality; and

persuasion and message acceptance reflect the personal focus and tailoring that AI systems add through personalized recommendations and perceived credibility. Message reception is a precondition for the others, because a message that is not received cannot be interpreted, accepted, or acted upon. In this sense, the six dimensions are intended as a process-based representation of how employees experience AI-generated messages, from delivery through to behavioral response.

The six dimensions are not presented as an exhaustive inventory of AI-based communication. Other attributes, such as the transparency or explainability of AI outputs, information overload, and interface design, are not measured separately, and the dimensions capture employees' perceptions of the AI tools deployed at UDN (dashboards, automated alerts, and the chatbot) rather than system-level performance data. These limits are revisited in Section 6.

Information Exchange

Information exchange refers to the extent to which AI systems deliver accurate, relevant, and timely data in a structured manner (Janakiraman et al., 2023). AI-driven dashboards and integrated systems consolidate fragmented data into coherent formats, reducing informational noise and lowering uncertainty in decision-making, which supports faster task completion and fewer coordination errors (Baan et al., 2023). Therefore, the following hypothesis is proposed:

H1: Information exchange is positively associated with work performance.

Message Reception

Message reception concerns whether AI-mediated communication is reliably delivered and acknowledged by intended recipients. AI-based notifications, escalation mechanisms, and automated alerts enhance the immediacy and salience of communication, improving situational awareness and reducing delays that could otherwise compromise performance (Sapkota et al., 2025). Therefore, the following hypothesis is proposed:

H2: Message reception is positively associated with work performance.

Message Understanding and Feedback

This dimension reflects employees' ability to accurately interpret information and obtain clarification when needed (Xavier, 2002). AI-enabled chatbots, guided prompts, and interactive interfaces simulate the feedback immediacy emphasized by MRT, reducing misinterpretation and rework (Morris & Maes, 2026). Therefore, the following hypothesis is proposed:

H3: Message understanding and feedback are positively associated with work performance.

Message Acceptance

Message acceptance reflects employees' trust in, and willingness to act upon, AI-generated communication (Hernández-Tamurejo et al., 2025; Montealegre-López, 2025). When AI systems consistently deliver accurate and transparent information, employees perceive the medium as credible, which supports behavioral alignment rather than resistance (Rice, 1992). Therefore, the following hypothesis is proposed:

H4: Message acceptance is positively associated with work performance.

Persuasion

Persuasion refers to AI-based communication's capacity to influence employees' decisions and behavior. Systems that present predictive insights, comparative analytics, and data-backed recommendations supply cognitive cues that shape decision-making and can strengthen execution discipline (Herath Pathirannehelage et al., 2025). Therefore, the following hypothesis is proposed:

H5: Persuasion is positively associated with work performance.

Reaction Provocation

Reaction provocation captures the extent to which AI-based communication stimulates timely and proactive responses. Automated alerts, anomaly detection, and escalation triggers shorten the interval between message transmission and behavioral response, helping to prevent escalation of operational issues (Li et al., 2025). Therefore, the following hypothesis is proposed:

H6: Reaction provocation is positively associated with work performance.

Existing research predominantly examines AI's effect on organization-level outcomes such as productivity, innovation capability, and financial performance, with comparatively limited attention to individual-level work performance (Zahs & Schmodde, 2026). Although MRT has been widely applied to traditional and digital channels, its integration with AI-based communication systems such as chatbots and automated decision-support tools remains underdeveloped (Ishii et al., 2019). Moreover, empirical studies rarely disaggregate AI-based communication into functional dimensions as examined here, instead focusing on technology acceptance, satisfaction, or usability (Laumer et al., 2017). Finally, performance outcomes are often broadly defined, with limited empirical evidence linking specific AI-based communication processes to concrete, individual-level indicators such as reduced time, cost, and conflict. This study addresses that gap using data from a safety-critical utility setting.

METHODOLOGY

A Quantitative Case Study

This study adopts a quantitative case study design to examine how AI-based communication is related to employees' work performance within a single, purposively selected organizational setting, namely UDN, the distribution network division of a national electricity utility. The case study approach was chosen because UDN represents a theoretically relevant and information-rich setting: it is a safety-critical, digitally transforming utility operation in which employees routinely depend on AI-mediated communication (dashboards, automated alerts, and an AI chatbot) to coordinate maintenance, respond to outages, and maintain service continuity. Rather than relying on qualitative case description, the study operationalizes the case quantitatively: constructs are measured with multi-item scales adopted from prior research, and hypothesized relationships are tested statistically using correlation and multiple regression across 180 respondents drawn from the case organization. This design is appropriate because the study aims to measure relationships between clearly defined constructs using numerical indicators that can be analyzed statistically (Creswell & Creswell, 2018; Lim, 2025), while preserving the contextual richness of a single, safety-critical organizational case (Yin, 2018). Data were collected in a single cross-sectional survey from November 2025 to January 2026, which was appropriate given that UDN is in an active digitalization phase and employees' perceptions of AI-based communication can be captured accurately within this window. Because the design is cross-sectional and confined to one organization, it supports the examination of associations among variables but not causal inference or generalization beyond similar settings (see Section 6).

Case Context, Population, and Sampling

The case organization, UDN, is the distribution network division of a national electricity utility responsible for delivering electricity from transmission substations to end users. As the organizational unit closest to consumers, UDN manages network planning, asset maintenance, outage restoration, meter operations, and safety compliance through a geographically dispersed workforce of engineers, technical personnel, and operational staff. Ongoing digital-transformation initiatives have accelerated UDN's adoption of AI-based communication platforms, including a predictive asset-analytics tool, an advanced distribution management system, a smart-metering operations platform, and an AI-based chatbot, which have reshaped how employees receive alerts, interpret operational data, and execute technical tasks.

The population comprised approximately 10,833 full-time UDN employees who interact with AI-based communication systems in the course of their work, spanning both technical roles which primarily interact with predictive maintenance alerts and system dashboards and non-technical, administrative, and managerial roles (which primarily use AI-supported reporting tools and automated notifications). As suggested by Kang (2021), sample size was determined using G*Power for multiple regression with six factors, an alpha level of .05, statistical power of .80, and a medium effect size ($f^2 = .15$), yielding a minimum required sample of approximately 98 respondents. To strengthen reliability and allow for incomplete responses, the study targeted a minimum of 110 respondents; the achieved sample was 180. A stratified random sampling technique was used, with the population stratified by job function (technical vs. non-technical) and respondents drawn proportionately from each stratum to ensure representativeness across functional roles.

Measurement Instrument

Data were collected using a structured, self-administered questionnaire comprising two sections. The first section measured AI-based communication across six dimensions: information exchange, message reception, message understanding and feedback, message acceptance, persuasion, and reaction provocation, using three items per dimension (18 items total). The second section measured work performance using three items addressing cost reduction, timeliness of collaboration, and reduction of workplace conflict. The instrument was adopted from Florea and Croitoru (2025), whose items were developed from the AI and organizational communication literature and refined through expert review and pilot testing. The rationale for the six dimensions is set out in Section 2.3. A demographic section captured gender, age group, job scope, years of service, education level, and work location (urban/rural). All items were assessed on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Data Collection Procedure

The questionnaire was distributed online via Google Forms to UDN employees who interact with AI-based communication tools in their daily work. Respondents were informed of the study's purpose, assured of confidentiality, and required to provide informed consent before proceeding; participation was voluntary throughout. Reminders were sent to encourage participation and improve response rates.

Data Analysis Technique

Descriptive statistics summarized respondent demographics and construct-level means and standard deviations. Internal consistency reliability was assessed using Cronbach's alpha, with values of .70 or above considered acceptable (Taber, 2018). Pearson correlation examined the strength and direction of bivariate relationships between the six AI-based communication dimensions and work performance. Multiple linear regression was then used to estimate the unique contribution of each dimension to work performance while controlling for the others, using the coefficient of determination (R^2), standardized beta coefficients, t-statistics, and the overall F-test to evaluate model fit and significance. Because the predictors were expected to be strongly intercorrelated, multicollinearity was examined through tolerance and variance inflation factor (VIF) values computed from the predictor correlation matrix, with VIF values below 5 regarded as acceptable (Hair et al., 2022) and interpreted alongside the cautions of O'Brien (2007). Given the cross-sectional, single-source data, all results are interpreted as associations rather than causal effects.

Ethical Considerations

The study adhered to standard ethical safeguards for organizational research. Participation was voluntary and preceded by informed consent; no personally identifiable information (names, employee numbers, email addresses, or departmental codes) was collected, and all data were analyzed in aggregate to prevent individual identification. Formal approval was obtained from UDN's Human Resources function prior to internal distribution of the survey, and participants were assured that the research would not interfere with their job performance or reporting lines. All data were stored securely and used solely for academic purposes.

RESULTS

Respondent Profile

A total of 180 UDN executives participated in the survey. Table 1 summarizes the demographic profile of respondents.

Table 1. Demographic Profile of Respondents (N = 180)

Variable	Category	n	%
Gender	Male	107	59.4
	Female	73	40.6
Age group	20–29	34	18.9
	30–39	84	46.7
	40–49	42	23.3
	Over 50	20	11.1
Job scope	Technical	167	92.8
	Non-technical	13	7.2
Years of service	Less than 5 years	40	22.2
	5–10 years	40	22.2
	10–20 years	80	44.4
	More than 20 years	20	11.1
Education level	Bachelor's degree	137	76.1
	Diploma	15	8.3
	Master's degree	28	15.6
	PhD	0	0.0
Work location	Urban area	140	77.8
	Rural area	40	22.2

The sample was predominantly male (59.4%) and concentrated in the 30–39 age band (46.7%). Consistent with proportionate stratified sampling, technical employees made up the large majority of respondents (92.8%), reflecting their relative share of the broader UDN workforce. Most respondents held a bachelor's degree (76.1%) and worked in urban locations (77.8%), indicating a reasonably well-educated, urban-concentrated executive population with substantial organizational tenure (77.8% with five or more years of service).

Descriptive Statistics for Study Constructs

Table 2 presents the mean and standard deviation for each of the six AI-based communication dimensions and for work performance, each measured with three items on a five-point scale.

Table 2. Descriptive Statistics for Study Constructs (N = 180)

Construct	Items	Mean	SD
Information Exchange (IE)	3	4.26	0.58
Message Reception (MR)	3	4.26	0.57
Message Understanding & Feedback (MUF)	3	4.17	0.54
Message Acceptance (MA)	3	4.19	0.51
Persuasion (PS)	3	4.17	0.57
Reaction Provocation (RP)	3	4.29	0.52
Work Performance (WP)	3	4.24	0.59

All constructs recorded mean scores above 4.0 on the five-point scale (range 4.17–4.29), indicating that respondents generally perceived AI-based communication favorably across all six dimensions and reported comparatively high work performance. Standard deviations were modest (0.51–0.59), suggesting relatively consistent perceptions across the sample. Such uniformly favorable responses may also reflect a general response tendency, a possibility considered in Section 4.5.

Reliability Analysis

Internal consistency was evaluated using Cronbach's alpha. As shown in Table 3, all seven constructs exceeded the recommended threshold of .70 (Taber, 2018), with values above .90, indicating excellent internal consistency.

Table 3. Internal Consistency Reliability

Construct	Items	Cronbach's α	Interpretation
Information Exchange (IE)	3	.952	Excellent
Message Reception (MR)	3	.951	Excellent
Message Understanding & Feedback (MUF)	3	.915	Excellent
Message Acceptance (MA)	3	.922	Excellent
Persuasion (PS)	3	.927	Excellent
Reaction Provocation (RP)	3	.904	Excellent
Work Performance (WP)	3	.912	Excellent

Correlation Analysis

Pearson correlation analysis examined bivariate relationships among the six AI-based communication

dimensions and work performance (Table 4). All communication dimensions were positively and significantly correlated with work performance ($p < .01$). Persuasion showed the strongest association with work performance ($r = .826$), followed closely by information exchange ($r = .821$), message reception ($r = .793$), and message understanding and feedback ($r = .775$). Reaction provocation ($r = .713$) and message acceptance ($r = .711$) also showed strong, significant correlations, though somewhat lower than the other dimensions. The predictors were also strongly interrelated ($r = .599$ to $.822$). This is consistent with their shared conceptual grounding in communication richness, but it also raises the possibility of overlap among the dimensions, which is examined in Section 4.5.

Table 4. Pearson Correlation Matrix

Variable	1	2	3	4	5	6	7
1. Work Performance	—						
2. Information Exchange	.821**	—					
3. Message Reception	.793**	.773**	—				
4. Message Understanding & Feedback	.775**	.750**	.736**	—			
5. Message Acceptance	.711**	.680**	.733**	.822**	—		
6. Persuasion	.826**	.792**	.796**	.783**	.740**	—	
7. Reaction Provocation	.713**	.695**	.733**	.745**	.721**	.599**	—

Note. ** $p < .01$ (two-tailed). $N = 180$.

Multiple Regression Analysis

Multiple linear regression was conducted with the six AI-based communication dimensions entered simultaneously as predictors of work performance. The overall model was statistically significant, $R = .889$, $R^2 = .791$, adjusted $R^2 = .784$, $F(6, 173) = 109.199$, $p < .01$, indicating that the six dimensions collectively accounted for 79.1% of the variance in work performance. Table 5 presents the individual regression coefficients.

Table 5. Summary of Regression Coefficients (Dependent Variable: Work Performance)

Predictor	B	β (std.)	t	p	Result
Information Exchange	0.279	0.271	4.121	$< .01$	Significant
Message Reception	0.138	0.132	1.893	.060	Not significant
Message Understanding & Feedback	0.123	0.111	1.488	.139	Not significant
Message Acceptance	-0.043	-0.037	-0.556	.579	Not significant
Persuasion	0.368	0.350	4.764	$< .01$	Significant
Reaction Provocation	0.185	0.162	2.618	.010	Significant

Note. $R = .889$, $R^2 = .791$, Adjusted $R^2 = .784$, $F(6, 173) = 109.199$, $p < .01$.

Of the six dimensions, only information exchange ($\beta = .271$, $p < .01$), persuasion ($\beta = .350$, $p < .01$), and

reaction provocation ($\beta = .162$, $p = .010$) emerged as statistically significant unique predictors of work performance when all dimensions were considered simultaneously. Message reception ($\beta = .132$, $p = .060$), message understanding and feedback ($\beta = .111$, $p = .139$), and message acceptance ($\beta = -.037$, $p = .579$) did not reach significance, despite each showing a strong positive bivariate correlation with work performance. This pattern suggests that shared variance among the highly intercorrelated predictors (Table 4) reduces the unique explanatory contribution of message reception, understanding/feedback, and acceptance once information exchange, persuasion, and reaction provocation are accounted for.

Table 6. Collinearity Diagnostics and Relative Importance of the Predictors for Work Performance

Predictor	Tolerance	VIF
Information Exchange	.279	3.58
Message Reception	.249	4.01
Message Understanding & Feedback	.217	4.60
Message Acceptance	.270	3.71
Persuasion	.223	4.48
Reaction Provocation	.317	3.15

Because the six dimensions were strongly intercorrelated (Table 4), collinearity diagnostics were computed from the correlation matrix of the predictors (Table 6). Tolerance values ranged from .217 to .317, and VIF values ranged from 3.15 to 4.60. These values are below the conventional cut-off of 5 (Hair et al., 2022) and below the rule of 10 (O'Brien, 2007), so collinearity was not severe by conventional standards.

Summary of Hypothesis Testing

Table 7. Summary of Hypothesis Testing

Hypothesis	β	p	Decision
H1: Information exchange $\rightarrow$ Work performance	0.271	< .01	Supported
H2: Message reception $\rightarrow$ Work performance	0.132	.060	Not supported
H3: Message understanding & feedback $\rightarrow$ Work performance	0.111	.139	Not supported
H4: Message acceptance $\rightarrow$ Work performance	-0.037	.579	Not supported
H5: Persuasion $\rightarrow$ Work performance	0.350	< .01	Supported
H6: Reaction provocation $\rightarrow$ Work performance	0.162	.010	Supported

Three of the six hypotheses (H1, H5, and H6) were supported, indicating that information exchange, persuasion, and reaction provocation each show a statistically significant, positive association with work performance after controlling for the other dimensions. Hypotheses H2, H3, and H4 were not supported in the regression model, although the corresponding constructs remained significantly and positively correlated with work performance at the bivariate level. Given the collinearity discussed in Section 4.5, the lack of support for H2, H3, and H4 does not mean that these dimensions are unrelated to performance.

DISCUSSION

The findings indicate that AI-based communication is positively associated with work performance across all six dimensions examined, but that only three dimensions (information exchange, persuasion, and reaction provocation) were unique predictors of performance once shared variance among the dimensions is accounted for. This pattern is consistent with the interpretation that AI-based communication is associated with higher employee-level performance mainly where it (a) supplies clear and continuous information, (b) actively influences employee behavior toward action, and (c) triggers timely responses, rather than where messages are only delivered, understood, or accepted in isolation. Because the data are cross-sectional and come from one organization, this interpretation describes associations and not causal mechanisms.

Information exchange's significant association with performance ($\beta = .271, p < .01$) is consistent with MRT's core proposition that reducing equivocality through structured, accurate, and timely information is related to better task execution. In UDN's operational context, dashboards and integrated platforms that consolidate fragmented data may help employees make faster, more informed decisions and reduce ambiguity and coordination delays, although the present data cannot confirm this mechanism.

Persuasion emerged as the strongest predictor ($\beta = .350, p < .01$), suggesting that AI communication may be most effective when it goes beyond delivering information to actively guiding employees toward specific actions, for example, through recommendations, prioritized risk indicators, or behavioral nudges. This finding suggests that MRT could be extended by treating persuasive capacity, rather than richness alone, as a performance-relevant mechanism in AI-mediated environments.

Reaction provocation was also a significant predictor of performance ($\beta = .162, p = .010$), consistent with the premise that AI-generated alerts and triggers that prompt immediate responses may help employees act quickly and prevent escalation of operational issues, a property with particular relevance in a safety-critical utility environment where delays can compound into larger service disruptions.

By contrast, message reception, message understanding and feedback, and message acceptance, while positively and significantly correlated with performance at the bivariate level, did not retain unique predictive power in the full regression model. This does not imply these processes are unimportant; rather, it suggests they may function as necessary but not independently sufficient conditions; that is, employees must receive, understand, and be willing to accept AI-generated communication before persuasion and reaction provocation can translate into action, but once information exchange, persuasion, and reaction provocation are modeled together, these earlier-stage processes show little unique explanatory power, which is likely to reflect their high intercorrelation with the other dimensions ($r = .599$ to $.822$ in Table 4). The collinearity diagnostics and dominance analysis (Table 6) support this reading: the VIF values of 3.15 to 4.60 indicate moderate overlap, and message reception and message understanding and feedback each account for a larger share of explained variance than reaction provocation, even though only reaction provocation had a significant coefficient. The "necessary but not sufficient" account remains a theoretical interpretation that this cross-sectional design cannot test directly. An equally plausible explanation is that the earlier-stage and later-stage dimensions are not fully distinct in this sample.

The findings offer a tentative extension of Media Richness Theory into AI-mediated organizational environments. They are consistent with the view that AI systems can function as active communication agents rather than passive channels, although this study did not test that proposition directly. Whereas traditional MRT explains effectiveness primarily in terms of human-selected media richness, the findings suggest that persuasive capacity and the ability to provoke timely reactions may be performance-relevant mechanisms that go beyond the theory's original richness dimensions, pointing to a possible refinement of how MRT applies in AI-rich environments that future research should test.

The findings have practical implications for organizations deploying AI-based communication in safety-critical or operationally complex settings. They suggest several priorities, which should be confirmed in further research before being treated as firm recommendations. First, unifying fragmented AI-driven information sources (dashboards, predictive analytics, operational platforms) into a coherent interface, with

standardized formats and improved visual clarity, may enhance information exchange and reduce decision time and cost. Second, because persuasion was the strongest predictor of performance, AI-generated messages could incorporate actionable recommendations, risk indicators, and clear calls to action, potentially supplemented with behavioral nudges such as urgency cues. Third, strengthening reaction-provocation mechanisms, for example, through prioritized high-risk alerts, automated escalation protocols, and response-tracking, may reduce delays and prevent minor issues from escalating. Finally, given that message reception, understanding, and acceptance remain foundational processes, organizations should invest in intelligent message prioritization to curb information overload and in employee training that builds AI-communication literacy, which may help technological investment translate into measurable performance gains.

CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

This quantitative case study examined how six dimensions of AI-based communication relate to employees' work performance within the distribution network division of a national electricity utility. All six dimensions were positively correlated with work performance, but regression analysis showed that only information exchange, persuasion, and reaction provocation were significant unique predictors of performance. Together, the six dimensions accounted for 79.1% of its variance, most of which was shared among them; this figure is probably inflated by common method variance and overlap among the dimensions. These results suggest that, in this case, AI-based communication is more strongly associated with performance when it clarifies informat-

ion, actively influences employee behavior, and triggers timely action than when it only delivers messages. The findings offer a preliminary extension of Media Richness Theory into AI-mediated organizational communication and a tentative basis for prioritizing AI communication design in information consolidation, persuasive messaging, and responsive alerting, which may help translate digital transformation into employee-level performance gains.

As a single-organization, cross-sectional case study, this research captures relationships at one point in time within one utility setting, which limits causal inference and generalizability beyond similar organizational contexts. The relationships reported here are therefore associations; the direction of influence cannot be established, and employees who perform well may also evaluate AI-based communication more favorably. Future research should adopt longitudinal designs to examine how these relationships evolve as employees gain experience with AI systems and as those systems mature. The reliance on self-reported perceptual data collected from the same respondents at the same time also introduces potential response bias and common method variance, which may have inflated the associations and the high R^2 ; incorporating objective performance indicators (e.g., task completion time, operational error rates, service-restoration metrics) alongside perceptual measures would strengthen construct validity. The six dimensions were strongly intercorrelated, and their convergent and discriminant validity were not formally assessed in this study, so the dimensions may not be empirically distinct. Future research should test the measurement model and use approaches suited to overlapping predictors, such as structural equation modeling or relative-importance analysis. In addition, the six dimensions were drawn from an existing framework and do not exhaust the features of AI-based communication, which also include, for example, transparency, explainability, and information overload. Finally, because 92.8% of respondents were technical staff, the results may not represent non-technical roles. Because the case is confined to a single electricity distribution utility, the results may be context-specific; replicating the study across other utilities, industries, or a multi-case comparative design would improve external validity and allow cross-context comparison. The exclusively quantitative approach, while enabling statistical generalization within the case, does not capture the underlying reasons why message reception, understanding, and acceptance failed to predict performance independently; a mixed-methods extension incorporating interviews or focus groups could illuminate these mechanisms. Future studies should also test mediating and moderating variables such as trust in AI, organizational culture, leadership support, and digital readiness, and examine multi-level outcomes including team- and organization-level performance in addition to the individual-level focus adopted in this study.

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Conflict of Interest Statement

The authors declare that there is no conflict of interest. The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

Authors' Contributions

Firza Sulaiman: Conceptualization, design, formal analysis, investigation and writing-original draft; **Nasrudin Baidi and Azleen Ilias:** Conceptualization, writing- review and editing, and validation.

Declaration of Generative AI in the Writing Process

During the preparation of this manuscript, the authors used AI tools to improve grammar, sentence structure, clarity, and academic readability. All research ideas, analysis, and judgement remain entirely the authors' own. The authors have thoroughly reviewed and verified all AI-assisted revisions and take full responsibility for the integrity, accuracy, and originality of the submitted manuscript.

Data Availability/Supplementary Materials

This study's data were gathered via a survey. Participants were informed that participation was voluntary and that their data would remain private and confidential. Only those who consented to these conditions completed the survey. Because of confidentiality agreements, the dataset is not publicly accessible but can be requested from the corresponding author under reasonable terms.

Ethics Statement

This research adhered to the university's guidelines. All participant-related procedures ensured confidentiality, anonymity, and informed consent. No ethical concerns arose during the study.

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