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The Impact of AI-Generated Corporate Messaging as a Credibility Signal in Algorithmic Communication

Abstract

Generative AI (Artificial Intelligence) mechanisms such as Gemini, Microsoft Copilot, Grammarly, and more are becoming a significant part of message creation in organisations. However, algorithmic bias creates an ethical, psychological, and strategic dilemma for organisational employees. In this research, the authors explored the impact of automation, authenticity, and trust in corporate messaging on employees' perceived corporate credibility, transparency, and integrity. The authors used a mixed methodology. A survey study was conducted with 246 participants. Further, semi-structured interviews were performed with communication and marketing executives. The research was grounded in Signalling Theory, TAM (Technology Acceptance Model) and Media Richness Theory. The results revealed that while AI helps organisations with communication efficiency, precision and personalisation, it also creates a “credibility gap”, reducing authenticity and accountability. For practical purposes, this research suggests applying co-creation to maintain corporate credibility in the era of algorithmic communication by connecting human creativity with AI-assisted mechanisms.

This research contributes to the continued discourse on technological advancements, generative AI and human authenticity in a continuously changing corporate ecosystem.

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1. Introduction

Artificial intelligence (AI) continues to change corporate communication, and it impacts how today's organizations define, organize, create, personalize and communicate their messages to their stakeholders (Kalogiannidis et al., 2024; Awaludin & Aravik, 2025; García-Orosa et al., 2023). Besides, AI in the era of digital communication offers opportunities for content curation, relationship-building, and information exchange (Baig et al., 2024). According to PwC and Gartner, by 2030, approximately 81% of global corporations are expected to use AI in content generation for algorithmic communication. However, while new technologies could offer efficiency, scalability, and accuracy, they create ethical and psychological challenges regarding authenticity, trust, and human oversight (Baig et al., 2024; Hohenstein et al., 2023; Kalogiannidis et al., 2024).
AI-generated communication is not limited to chatbots or automated responses but extends to press releases, annual reports, and more (Esposito, 2022; Sundar & Lee, 2022). According to Hohenstein et al. (2023), generative AI is well positioned to change how we communicate. Moreover, AI mechanisms like ChatGPT continue to be used to generate text messages and social media posts for organizations. Corporate stakeholders treat internal or external communication as authentic, and trustworthy in corporate messaging, where transparency promotes openness, communication, and responsibility, enabling open information exchange (Park & Yoon, 2024). Consequently, messages or communication altered by AI could impact corporate integrity. These days, user-generated, brand-generated and AI-generated content discourse has already created a space or ecosystem for continues discourse.
The continues adoption of AI in organizations creates a boundary between human and machine-generated content. Additionally, it creates uncertainty between stakeholders regarding message credibility and intent (Dwivedi et al., 2023). Notably, 63% of consumers worry about the lack of transparency in AI-assisted brand communication, while 57% report reduced trust when organizations fail to report AI in their content (Accenture, 2023).In this research, the authors explored the impact of automation, authenticity, and trust in corporate messaging and how it impacts employees perceived corporate credibility, transparency, and integrity. The authors used a mixed methodology. First survey was prepared and executed using Qualtrics software. Moreover, data was analyzed using SPSS30 statistics. Moreover, the authors conducted semi-structured interviews via Zoom. Data was transcribed via Otter.ai. Additionally, this research was grounded in Signaling Theory, Media Richness Theory, and Ethical AI frameworks. Next sections bellow will show the results of these processes.

2. Literature Review

Artificial intelligence is gradually permeating all areas of life, and corporate communication is no exception (Awaludin & Aravik, 2025; Getchell et al., 2022). AI-generated corporate messages, news and other content are increasingly appearing in the media, on social networks, in advertising, on company websites, and across other media channels (Baig et al., 2024; Bankins et al., 2024). This technology is fundamentally transforming organizational communication while providing opportunities to improve customer service, optimize internal processes, and make better decisions (Hassan, 2024; Garcia et al., 2024). Moreover, artificial intelligence tools increase communication efficiency by enabling faster information transfer, automating repetitive tasks, facilitating continuous interaction, and ensuring accessibility regardless of location or time (Sovianti & Novrian, 2024; Csaszar & Steinberger, 2022). Importantly modern consumers live in an era of personalized content, and AI technologies such as machine learning and natural language processing enable content personalization, and efficiency (Abed & Farrokhi, 2025; García-Orosa et al., 2023; Lim & Schmälzle, 2024). Artificial intelligence helps organizations improve communication not only with external consumers but also with internal stakeholders (Bankins et al., 2024). Research shows that AI significantly enhances internal organizational communication, which directly improves employee performance (García-Orosa et al., 2023).

AI most strongly reinforces such communication elements as information transmission, message reception, comprehension, and the elicitation of responses (Csaszar & Steinberger, 2022). This transforms organizational communication, increases productivity, and reduces errors (Florea & Croitoru, 2025). However, message-generation opportunities that opened by developing technologies may also pose challenges for organizations, for example, when hiring content creators (Esposito, 2022). Some authors argue that in text writing AI makes everyone appear competent which in the future forces to use special mechanisms to assess message authenticity and job candidates' competence (Gans, 2024; Hohenstein et al., 2023; Lynch et al., 2023). This may further encourage the development of artificial intelligence technologies in the field of corporate communication.

To increase communication efficiency and create messages, organizations most often rely on generative artificial intelligence (Getchell et al., 2022; Garcia et al., 2024). This is an advanced type of artificial intelligence that creates new, original content analyzes data, writes computer codes, performs customer service functions, and carries out other communication-related tasks (Baig et al., 2024; Gil de Zúñiga et al., 2024). This technology generates new information by analyzing data and using complex deep learning models (Grewal, 2025).

Generative AI is an advanced form of algorithmic communication which determines to whom, when, and through which channel generated content is delivered (García-Orosa et al., 2023). Algorithmic communication describes a phenomenon in which algorithms participate in information exchange, filter information, and decide what to show to users, thereby influencing their social, economic, and political behavior (Laapotti & Raappana, 2022). Schumann and Taddicken (2021) identified four main roles of algorithms in communication: information filtering; prioritization based on user behavior and predicted relevance; classification, whereby information is assigned to specific categories; and association building, when users are presented with similar types of content. Together, these technologies change the nature of communication by increasing automation and personalization (Getchell et al., 2022). At the same time, they raise issues of transparency, accountability, and trust in communication (Hohenstein et al., 2023; Jones-Jang & Park, 2023; Garcia et al., 2024; Muldoon & Raekstad, 2023). For this reason, it is important to study how audiences perceive credibility, authenticity, and organizational reputational integrity, and what ethical, psychological, and strategic consequences arise for organizations when their messages are created by artificial intelligence rather than humans.

A broad range of scientific research shows that the use of generative artificial intelligence requires transparency, accountability, and critical understanding on a global scale to ensure that the impact of these technologies is positive and does not harm society or stakeholders, regardless of the field or nature of activity (Esposito, 2022). In the context of algorithmic communication and AI-generated organizational messages, it is observed that ethical issues could be mitigated by adopting a responsible approach and integrating technological safeguards (Hohenstein et al., 2023; Naidoo & Dulek, 2022). This could be achieved by ensuring human oversight in the creation of AI-generated messages, increasing transparency by indicating that content was created using AI, managing risks of bias and misinformation, conducting audits and continuous monitoring, establishing clear ethical guidelines, or implementing accountability mechanisms (Khan & Saravanan, 2025; Getchell et al., 2022). According to Zhang et al. (2025) and García-Orosa et al. (2023), there are eleven key ethical principles are identified such as beneficence, dignity, freedom and autonomy, justice and fairness, non-maleficence, privacy, responsibility, solidarity, sustainability, transparency, and trust. It is important to emphasize that these principles are not specifically oriented towards the field of corporate communication (Gil de Zúñiga et al., 2024).

Moreover, literature frequently argues that transparency can help reduce ethical, psychological, and strategic consequences for organizations, recent research shows that transparency is not always automatically beneficial as it can harm trust (Baig et al., 2024). Therefore, organizations must carefully decide when, how, and to whom they disclose the use of artificial intelligence (Schilke & Reimann, 2025). Studies also show that the use of artificial intelligence in creating communication content reduces brand authenticity in the eyes of consumers, which can negatively affect not only their attitudes but also their behavior. Moroever, research by Brüns and Meißner (2024) and Neumann et al. (2024) revealed that consumer reactions mitigate when AI merely contributes to content creation rather than creating it entirely. This suggests that to maintain consumer trust organizations should apply AI tools cautiously in the creation of communication messages or use them only partially (Csaszar & Steinberger, 2022; Garcia et al., 2024).

Another important ethical aspect of AI-generated corporate messages in the context of algorithmic communication is authenticity (García-Orosa et al., 2023). This organizational trait is highly valued by consumers, who expect corporate messages to reflect the organization's true values and emotions (Perifanis & Kitsios, 2023). Research shows that AI-created and disclosed factual content generally does not harm organizations; however, emotional messages that are known or suspected to have been written by AI are perceived as inauthentic and reduce consumer trust as well as loyalty (Kirk & Givi, 2025; Jones-Jang & Park, 2023; Hohenstein et al., 2023; Awaludin & Aravik, 2025). This once again confirms that companies must strategically assess when and how to employ artificial intelligence in message creation to avoid losing authenticity – this is particularly relevant when seeking emotional connections with consumers and their loyalty (Bankins et al., 2024; Esposito, 2022; Shin et al., 2022).

When generating messages with the help of artificial intelligence, organizations should also consider psychological aspects (Csaszar & Steinberger, 2022; Karinshak et al., 2023). Here again, strategic use of AI in algorithmic communication is essential, as some organizational stakeholders are less familiar with AI or still distrust it. Kim et al., 2025) introduce the term "AI anxiety" to describe the phenomenon in which people experience stress due to the rapid spread of AI technologies, fearing job loss, privacy violations, misinformation, or content unreliability. Given that organizations have no means to filter such individuals out of their audiences, creators of AI-generated corporate messages should take these psychological aspects into account and develop content strategically and with all possible safety measures in place (Getchell et al., 2022). This would not only help strengthen stakeholder trust but also contribute to societal mental well-being. According to some studies, anxiety is experienced not only by consumers of AI-generated content but also by its creators (Hohenstein et al., 2023). Although anxiety does not determine creators' intention to use generative artificial intelligence for content creation, this negative emotion reduces belief in the usefulness of AI tools, thereby decreasing willingness to use them (Li et al., 2024; Esposito, 2022). Consequently, organizations that use AI-generated messages in their operations should pay attention not only to external stakeholders but also to internal ones, ensuring that employees responsible for content creation are informed about the benefits of these technologies, do not fear them, and are able to use them appropriately in daily activities (Gil de Zúñiga et al., 2024; Jones-Jang & Park, 2023; Kulkov et al., 2024). This could be achieved by introducing technologies gradually, encouraging their use, providing training, and establishing clear rules as well as usage policies.

Another important issue frequently mentioned in literature is privacy. Typically, discussions focus on violations of AI users' privacy; however, when it comes to AI-generated corporate messages, risks also arise for organizational data (Hohenstein et al., 2023; Garcia et al., 2024). This can occur, for example, when company's communication specialist uses AI tools for content creation and inputs private company information (Walke et al., 2025). Lee et al. (2025) identify a way in which generative AI tools may violate privacy by using user-input data and conversation histories. Although systems offer the possibility to opt out of data collection and usage practices, not all users are aware of such conditions or even know that such an option exists. Shroff (2024) notes that although AI tool developers claim to anonymize user-provided information, this process is not fully refined and lacks clear guidelines, meaning the risk of improper data use remains. This further confirms that organizations should invest in educating employees responsible for preparing corporate messages with the help of artificial intelligence about responsible use of this technology and the protection of sensitive organizational data (Hohenstein et al., 2023; Gabelaia, 2025; Gil de Zúñiga et al., 2024).

3. Research Methodology

This research used a mixed-methods approach to explore how automation, authenticity, and trust impact employees' perceptions of corporate credibility, transparency, and integrity in AI-generated corporate communication. This methodological approach offered statistical and contextual depth to the research.

A survey study was conducted through Qualtrics Software. Survey questions were designed using multiple-choice and Likert-scale formats. The authors used snowball and convenience sampling to obtain a rich study sample. A survey was shared only on professional LinkedIn groups, asking others within to reshare. Data were screened for completeness, response quality, and outliers. Internal consistency reliability was assessed using Cronbach's alpha, with all constructs exceeding the recommended threshold of $\alpha \geq .70$, showing satisfactory reliability. Moreover, construct validity was evaluated through correlations and regression analysis. To address potential common-method bias in the final dataset, respondent anonymity and item randomization were used. Hence, statistical diagnostics revealed that common-method bias did not significantly affect the results. SPSS30 was used for statistical analysis. Moreover, statistical analyses conducted were tests of normality, descriptive statistics, one-way ANOVA, Pearson correlations, and multiple regression.

Semi-structured interviews were conducted via Zoom. All 17 interviews were transcribed using otter.ai. Moreover, the authors used purposive sampling to ensure the sample comprised industry professionals. Furthermore, the author used a six-step thematic analysis to identify and define themes and patterns.

This research followed ethical guidelines. All respondents, whether through surveys or interviews, were informed about the research purpose and were advised to withdraw at any time they felt they needed to stop. All personal identification and respondent characteristics were hidden or coded. All recorded data was destroyed 30 days after the transcript and thematic analysis.

4. Results

4.1 Survey Results

The research was conducted between March 11, 2025, and October 22nd, 2025. The authors, over the course of this research, collected 311 responses. Before descriptive and inferential statistics, the dataset was cleaned using a sequential data-cleaning process, as illustrated in Table 1. At first, the authors removed cases with >20% missing items, resulting in 28 cases, reducing the dataset to 283. Second was duplicate screening, which removed 6 cases, yielding 277 cases. Furthermore, attention checks were performed. During this stage, 12 cases were excluded, leaving a dataset of 265 cases. Furthermore, because straight-line cases exhibited zero variance, 256 cases were removed. At last, 10 cases were removed due to unrealistically fast completion times, resulting in a final 246. These results show that 20.9% of cases were removed from the original dataset.

Table 1: Screening and Data Cleaning Summary (Developed by the Author)

Steps	Criterium/Rule	Removed	Remain
Raw Export	All collected responses	-	311
Missingness Screen	Removed cases missing > 20% information	28	283
Duplicate Screen	Removed duplicated entries (ID/IP/timestamp patterns)	6	277
Attention Checks	Removed failed attention-check cases	12	265
Straight lining	Removed items with zero variance across item blocks	9	256

Speeding	Removed unrealistically fast competition times	10	246

After the data cleaning process, the authors performed a test of normality. Normality assumptions were examined for all composite variables using skewness, kurtosis, and the Shapiro-Wilk test. The results are illustrated in Table 2. The results demonstrated that skewness values ranged between -0.06 to 0.18, while kurtosis from -0.65 to -0.30. This revealed no substantial deviation from normality. Moreover, the Shapiro-Wilk test was statistically significant for credibility (W = 0.981, p = .002), transparency (W = 0.986, p = .017), and integrity (W = 0.987, p = .030). While there were minor deviations with acceptable skewness and kurtosis (Table 2), parametric analysis was appropriate for inferential statistical analysis.

Table 2: Test of Normality (n = 246) (Developed by the Author)

Variable	Skewness	Kurtosis	W	*p*
Automation	0.14	- 0.33	0.991	.132
Authenticity	0.08	- 0.30	0.990	.076
Trust	0.18	- 0.48	0.989	.056
Credibility	-0.06	- 0.65	0.981	.002
Transparency	-0.06	- 0.60	0.986	.017
Integrity	0.10	- 0.52	.0987	.030

Next, the authors conducted descriptive analysis on IVs and DVs. The results are illustrated in Table 3. Hence, the results revealed that IVs showed moderate perceptions of automation (M = 2.88, SD = 0.89), authenticity (M = 2.87, SD = 0.92), and trust (M = 2.95, SD = 0.90). Moreover, DVs showed moderate central tendencies, with credibility (M = 2.91, SD = 1.02), transparency (M = 2.99, SD = 0.98), and integrity (M = 2.93, SD = 0.95). Consequently, the results suggested adequate variance and suitability for correlation and regression analysis.

Table 3: Descriptive Statistics (n = 246) (Developed by the Author)

Variable	*M*	*SD*	*Min*	*Max*
Automation	2.88	0.89	1.00	5.00
Authenticity	2.87	0.92	1.00	5.00
Trust	2.95	0.90	1.00	5.00
Credibility	2.91	1.02	1.00	5.00
Transparency	2.99	0.98	1.00	5.00
Integrity	2.93	0.95	1.00	5.00

Furthermore, the authors conducted a one-way ANOVA analysis. First, an ANOVA was performed to determine whether perceptions of corporate credibility, transparency, and integrity differed by education level. The results in Table 4a revealed that education level did not significantly predict perceptions of credibility, $F(2, 243) = 1.77, p = .172, \eta^2 = .014$. Moreover, there were no statistically significant differences for transparency, $F(2, 243) = 0.92, p = .398, \eta^2 = .008$, or integrity, $F(2, 243) = 1.61, p = .203, \eta^2 = .013$. Hence, the effect sizes across all results were small, suggesting that education level was less than 2% of the variance and showing limited practical significance.

Table 4a: One-way ANOVA with Education Level (n = 246) (Developed by the Author)

DV	df1	df2	F	p	η^2
Credibility	2	243	1.77	.172	.014
Transparency	2	243	0.92	.398	.008
Integrity	2	243	1.61	.203	.013

Second, the authors analysed whether perceptions of corporate credibility, transparency, and integrity differed by age group. The results from Table 4b reveal that age group did not significantly impact perceptions of credibility, $F(4, 241) = 0.96$, $p = .431$, $\eta^2 = .016$. Moreover, the effect of age group on transparency was also non-significant, $F(4, 241) = 1.84$, $p = .122$, $\eta^2 = .030$. The same pattern was observed for integrity, $F(4, 241) = 1.33$, $p = .260$, $\eta^2 = .022$. Therefore, while transparency showed marginal variability, effect sizes remained small. This suggested limited practical significance.

Table 4b: One-way ANOVA with Age Group (n = 246) (Developed by the Author)

DV	df1	df2	F	p	η^2
Credibility	4	241	0.96	.431	.016
Transparency	4	241	1.84	.122	.030
Integrity	4	241	1.33	.260	.022

To continue, the authors conducted Pearson's correlation analysis to measure relationship between variables. In the results, coefficients generated between ±0.50 and ±1 mean a strong correlation, between ±0.30 and ±0.49 mean a moderate correlation. Moreover, below +0.29 are considered as a weak correlation. And lastly, a value of 0 means no relationship. The results are illustrated in Table 5. The table demonstrated that automation was moderately correlated with credibility ($r = .40$, $p < .001$), transparency ($r = .37$, $p < .001$), and integrity ($r = .34$, $p < .001$). Moreover, authenticity showed strong positive correlations with credibility ($r = .48$, $p < .001$), transparency ($r = .49$, $p < .001$), and integrity ($r = .54$, $p < .001$). Furthermore, trust showed strong relationship with credibility ($r = .45$, $p < .001$), transparency ($r = .49$, $p < .001$), and integrity ($r = .46$, $p < .001$). Lastly, intercorrelations among predictors ranged between $r = .24$ and .43.

Table 5: Pearson's Correlation Matrix (n = 246) (Developed by the Author)

Variable	1	2	3	4	5	6
Automation	-					
Authenticity	0.27***	-				
Trust	0.24***	0.43***	-			
Credibility	0.40***	0.48***	0.45***	-		
Transparency	0.37***	0.49***	0.49***	0.42***	-	
Integrity	0.34***	054***	0.46***	0.52***	.45***	-

Note. *p < .05*, p < .01*, p < .001****

Table 6 illustrates the overall fit of the multiple regression models predicting corporate credibility, transparency, and integrity. The results demonstrated that the regression model predicting credibility was statistically significant, $F(7, 238) = 21.09$, $p < .001$, illustrating 38.3% of the variance ($R^2 = .383$, adjusted $R^2 = .365$). The transparency model was similarly significant, $F(7, 238) = 21.83$, $p < .001$, with an R^2 of .391 (adjusted $R^2 = .373$). Lastly, the integrity model showed the strongest explanatory power, $F(7, 238) = 22.55$, $p < .001$, demonstrating 39.9% of the variance ($R^2 = .399$, adjusted $R^2 = .381$). These results reveal that the combined impact of automation, authenticity, trust and demographic controls offer a strong explanatory framework to better understand perception towards algorithmic messaging in corporate communication.

Table 6: Multiple Regression Model Fit (n = 246) (Developed by the Author)

DV	F(df1, df2)	*p*	R²	Adj.R²
Credibility	21.09 (7, 238)	<.001	.383	.365
Transparency	21.83 (7, 238)	<.001	.391	.373
Integrity	22.55 (7, 238)	<.001	.399	.381

Table 7a demonstrated that automation significantly predicted credibility ($B = 0.298$, $SE = 0.062$, $\beta = .258$, $t = 4.77$, $p < .001$). While authenticity ($B = 0.335$, $\beta = .301$, $t = 5.19$, $p < .001$) and trust ($B = 0.296$, $\beta = .260$, $t = 4.56$, $p < .001$) also appeared as significant predictors. Moreover, doctoral education was associated with higher credibility perceptions compared to the bachelor's group ($B = 0.369$, $p = .021$), while age and professional experience were not statistically significant.

Table 7a: Multiple Regression Predicting Credibility (n = 246) (Developed by the Author)

Predictor	B	SE B	β	t	p	95% CI [LL, UL]
Education (Master vs Bachelor)	0.085	0.113	0.083	0.746	.456	[-0.139, 0.308]
Education (Doctorate vs Bachelor)	0.369	0.159	0.362	2.319	.021	[0.056, 0.682]
Age (Years)	0.001	0.005	0.006	0.115	.909	[-0.010, 0.011]
Experience (Years)	0.009	0.010	0.049	0.951	.343	[-0.010, 0.029]
Automation	0.298	0.062	0.258	4.772	< .001	[0.175, 0.420]
Authenticity	0.335	0.064	0.301	5.193	< .001	[0.208, 0.462]
Trust	0.296	0.065	0.260	4.555	< .001	[0.168, 0.424]

Table 7b demonstrated that authenticity was the strongest predictor of transparency ($B = 0.368$, $\beta = .339$, $t = 6.01$, $p < .001$), while trust ($B = 0.327$, $\beta = .296$, $t = 5.29$, $p < .001$) and automation ($B = 0.258$, $\beta = .233$, $t = 4.31$, $p < .001$) were next in line. Demographic predictors were non-significant, with p-values exceeding .30, supporting the dominance of perceptual variables in explaining transparency assessments.

Table 7b: Multiple Regression Predicting Transparency (n = 246) (Developed by the Author)

Predictor	B	SE B	β	t	p	95% CI [LL, UL]
Education (Master vs Bachelor)	0.112	0.109	0.109	1.027	.305	[-0.103, 0.327]
Education (Doctorate vs Bachelor)	0.121	0.153	0.120	0.789	.431	[-0.181, 0.422]
Age (Years)	0.004	0.005	0.040	0.805	.422	[-0.006, 0.014]
Experience (Years)	-0.002	0.009	-0.012	-0.238	.812	[-0.020, 0.016]
Automation	0.258	0.060	0.233	4.313	< .001	[0.140, 0.376]
Authenticity	0.368	0.061	0.339	6.012	< .001	[0.248, 0.489]
Trust	0.327	0.062	0.296	5.286	< .001	[0.205, 0.450]

Lastly, Table 7c revealed that trust ($B = 0.334$, $\beta = .308$, $t = 5.57$, $p < .001$) and authenticity ($B = 0.314$, $\beta = .304$, $t = 5.31$, $p < .001$) were the strongest predictors of integrity. Automation was also significantly ($B = 0.212$, $\beta = .198$, $t = 3.70$, $p < .001$). Moreover, neither age nor professional experience was statistically significant ($p > .23$).

Table 7c: Multiple Regression Predicting Integrity (n = 246) (Developed by the Author)

Predictor	B	SE B	β	t	p	95% CI [LL, UL]
Education (Master vs Bachelor)	0.038	0.104	0.037	0.362	.718	[-0.166, 0.242]
Education (Doctorate vs Bachelor)	0.147	0.146	0.147	1.004	.316	[-0.140, 0.434]
Age (Years)	-0.001	0.005	-0.012	-0.247	.805	[-0.011, 0.009]
Experience (Years)	0.011	0.009	0.061	1.191	.235	[-0.007, 0.029]
Automation	0.212	0.057	0.198	3.702	< .001	[0.100, 0.325]
Authenticity	0.314	0.059	0.304	5.309	< .001	[0.197, 0.431]
Trust	0.334	0.060	0.308	5.565	< .001	[0.216, 0.452]

4.2 Interview Results

The authors conducted semi-structures interviews between April 24th, 2025, and October 7th, 2025. The interviewees were selected through purposive sampling with communication and marketing executives to explore their perceptions with algorithmic communication in the organizations. Table 8 shows the interviewee profiles. Accordingly, 70.5% of interviewees had advanced degrees. Moreover, 82.3% of respondents had 10 or more years of industry experience. Additionally, interviewees were from different industries such as tech, marketing, finance, pharma and retail.

Table 8: Interviewee Profile (n = 17) (Developed by the Author)

Characteristic	Category	n	%
Education	Bachelor's	5	29.4
	Master's	9	52.9
	Doctorate	3	17.6
Years of Experience	5-9 years	3	17.6
	10-15 years	6	35.3
	16-20 years	5	29.4
	20+ years	3	17.6
Industry Representation	Tech/SaaS	5	29.4
	Marketing/Advertising	4	23.5
	Finance/Fintech	3	17.6
	Pharma	3	17.6
	Retail	2	11.8

Interviews were conducted via Zoom software. Recordings were then transcribed using otter.ai. Thus, interview transcripts were analyzed using thematic analysis using six-phase approach. First, the authors performed data cleaning and familiarization with extracted data. Second, initial coding was performed followed by theme generation, theme reviews, definition and reporting. Themes were identified and recorded based on their relevance and recurrence during the interviews rather than frequency alone. Table 9 shows the results of thematic analysis.

Table 9 shows that 82.4% reoccurring theme was efficiency gains from automation. Interviewees also noted the operational advantages of AI-generated messaging. Particularly, interviewees highlighted speed, scalability and cost efficiency. Moreover, executives often addressed automation as "inevitable", specifically in engaging with high-volume of communication demands in today's corporate world. According to interviewees, many digital-first organizations are heavily invested in AI-generated algorithmic communication. However, the results also showed that efficiency was framed as functional benefit rather than strategic. On the contrary, 76.5% interviewees shared concern that AI-generated contents lacked emotional depth. Moreover, it does not communicate in distinctive brand voice. Furthermore, interviewees noted that AI-generated messages were formulated or polished, doubting the sincerity in communication. It should be noted that this result connects to empirical findings, that shows that authenticity was a strong predictor of credibility, transparency and integrity.

Furthermore, 88.2% of interviewees highlighted and spoke about the trust in AI-generated communication. It was noted that trust depends on transparency and disclosure. Many interviewees noted that if AI is undisclosed, it limits the confidence in messaging and improves scepticism in algorithmic communication. At last, the trust was defined as conditional rather than automatic. On contrary, 94.1% of interviewees advocated for human-AI collaboration, stating that hybrid communication strategies could improve personalization, but notably humans must stay as editorial authorities. Notably, this theme was dominant consensus, suggesting that AI must be viewed as augmentative mechanism, not replacement for human communicators.

The last themes that frequently reoccurred with 70.6% was reputation risk and concerns. Interviewees noted the concerns for manipulation, misinformation and integrity erosion. Hence these risks were frequently associated to long-term brand trust rather than performance metrics. This result emphasizes the strategic role of ethical oversight in algorithmic communication.

Table 9: Thematic Analysis (n = 17) (Developed by the Author)

Theme	Key Patterns	n	%
Perceived Efficiency Gains from Automation	Faster content production, scalability, reduced operational costs	14	82.4

Authenticity Deficit in AI-generated messaging	Loss of brand voice, emotional flatness, "generic" tone	13	76.5
Trust and transparency	Need for disclosure, human oversight	15	88.2
Human-AI Collaboration as optimal model	Ao as support tool, human final control, hybrid workflow	16	94.1
Reputational risks and concerns	Fear of manipulation, credibility erosion, stakeholder backlash	12	70.6

5. Discussion

To show the research results and their relevance, the authors created an argumentative discussion grounded in Signaling Theory, TAM, and Media Richness Theory. First, in the context of AI-generated corporate messaging, signaling theory suggests that automation, authenticity, and trust perform as contesting and complementary signals. Survey results showed that automation positively predicted corporate credibility, transparency, and integrity, suggesting that AI use itself signals technological complexity and operational efficiency. Yet authenticity and trust consistently showed stronger effects across all results, indicating that how AI is used matters more than whether it is used at all. This was also visible in the interview results. According to Table 9, while majority of the executives recognized automation as an efficiency signal, others cautioned that AI-generated messaging risks signaling duplicity if not carefully managed or controlled. Additionally, they noted that trust depended on transparency and disclosure. This suggests that if automation is not disclosed in Algorithmic communication, trust may act as a negative signal. Lastly, the results indicate that AI does not necessarily replace traditional credibility signals but rather serves as conditional signaling. It could strengthen the organizational reputation, but if executed poorly or if AI-generated messaging is left unsupervised, the corporate value could decrease. Garcia et al., 2024), Gabelaia, 2025) (Hohenstein et al., 2023).

The integration of generative AI into corporate communication is becoming an essential part of algorithmic communication, fundamentally transforming internal and external message creation and dissemination practices (Bankins et al., 2024). While this technology helps organizations increase efficiency and offer greater personalization, it simultaneously raises ethical, psychological, and strategic issues (García-Orosa et al., 2023; Getchell et al., 2022). Reviewed academic studies highlight the importance of transparency, accountability, privacy, and trust, while also revealing that disclosing AI use does not always increase audience trust and may reduce perceived organizational authenticity (Wang et al., 2022). Meanwhile, psychological aspects such as "AI anxiety" influence both audience reactions and employees' attitudes toward AI use, compelling organizations to strategically evaluate the application of these technologies in different communication contexts (Yin et al., 2024). Thus, literature review reveals tension between the communicative benefits created by AI and potential reputational, trust-related, and ethical risks, justifying the need to study AI-generated corporate messages as a complex phenomenon of algorithmic communication (Baig et al., 2024; Jones-Jang & Park, 2023; Esposito, 2022; Lee et al., 2023).

Next, the authors addressed the Technology Acceptance Model (TAM) with perceived usefulness and ease of use. In today's technological and AI-led business ecosystem, employees' adaptability and readiness for algorithmic communication are significant. Firsthand, the results indicated that acceptance in corporate algorithmic communication is not purely instrumental. The survey data revealed that automation significantly impacts all corporate outcomes, endowing TAM's usefulness dimension. However, authenticity and trust showed more variance, suggesting that employees accept AI-generated messaging not only as a mechanism, but also as a representative of organizational values. Additionally, interviewees highlighted reputational consequences, risks, and perceptions, rather than ease of use. 94.1% of respondents favored human-AI collaboration. This suggests that TAM requires a perceived governance, and not just performance. Hence, it can be concluded that AI-generated algorithmic communication acceptance is less about usability and more about accountability, alignment, and intent.

Lastly, the authors argued that, according to the Media Richness theory, AI-generated corporate communication effectiveness relies on the capacity to disseminate complex information clearly. Hence, AI messages are low on richness due to low emotional and contextual adaptability. Survey results showed that authenticity and trust were the strongest predictors of transparency, indicating that corporate employees or stakeholders value rich, human-like communication. Additionally, 76.5% of executives stated that AI-generated messages were emotionally "flat", particularly in sensitive and personalized communication situations, where humanistic approaches are preferable. Therefore, these results support hybrid communication modes with MRT logic, which was seen by 94.1% of interviewees. This positions AI as a lean medium whose effectiveness depends on strategic human judgment

6. Conclusion

In this research, the authors explored the impact of automation, authenticity, and trust in corporate messaging on employees' perceptions of corporate credibility, transparency, and integrity when exposed to content generated by AI rather than humans. This research used a mixed-methods approach to extract and integrate numerical and psychological characteristics to better understand the extent of the research problem. Moreover, this research was strategically grounded in Signaling Theory, TAM, and Media Richness Theory.

This research revealed that perceptions of AI-generated algorithmic communication are created by integrating technological capabilities with relational meaning. The results demonstrated that while automation contributes positively to perceptions of corporate credibility, transparency, and integrity, authenticity and trust eventually override judgment. According to the survey results, strong and consistent effects were observed. Additionally, interview results revealed that executives agreed that AI must remain human-governed to avoid reputational liability.

Furthermore, by incorporating Signaling Theory, TAM, and Media Richness Theory, the results suggested that AI in corporate communication performs not as a mechanism, but as a symbolic actor whose legitimacy depends on transparency, intent, and communicative richness. Additionally, it was seen that automation without authenticity reduces trust, if driven by human oversight, it strengthens corporate legitimacy. Finally, these results position AI-generated content in algorithmic corporate communication as a socio-technical phenomenon. Moreover, the results emphasize the need for human-cantered AI governance in corporate communication strategies.

The results revealed that management should consider AI-generated corporate communication as a strategic mechanism that shapes corporate trust and legitimacy. Also, management should align communication strategies with message complexity, using automation for routine content while prearranging human-mediated, richer channels to protect corporate credibility, transparency, and integrity. Theoretically, this research adds to the existing literature and continues the discourse on algorithmic communication practices within organizations.

Future research should study the moderating roles of authenticity and trust through experimental designs for causal dynamics. Besides it would be practical to study how AI-generated communication differs across the cultural contexts. At last, future research must differentiate between types of communication to evaluate when AI-generated content is most and least appropriate in algorithmic messaging.

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