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Identification of Trust Determinants in LLM Technology Using the DEMATEL Method

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Marta Pawłowska-Nowak[1]

Abstract:

Purpose: *The study identifies determinants of trust in Large Language Model (LLM) technology among office employees using the DEMATEL method. It addresses a gap in understanding factors like credibility, user experience, and data security, which are crucial for AI adoption in workplaces.*
Design/Methodology/Approach: *The study employs a mixed-method approach, combining a literature review and empirical analysis using the DEMATEL method. The DEMATEL method was applied to develop causal-effect diagrams, identify prominence and relation indicators, and calculate the importance of individual factors. The methodology was chosen for its suitability in analyzing complex, interrelated variables.*
Findings: *The research identified the most significant determinants of trust in LLM technology. Key findings highlight that perceived credibility and accuracy of responses, prior experience with AI, and awareness of productivity impacts are the most influential factors. Additionally, user education, intuitive user interfaces, and robust data security were identified as crucial for building trust. These factors underscore the importance of transparency, usability, and reliability in fostering employee confidence in LLM technology.*
Practical Implications: *Organizations can enhance LLM adoption by ensuring credible outputs, providing training, and addressing data security. The results support trust-building strategies for sectors dependent on AI decision-making.*
Originality/Value: *This study offers a novel application of the DEMATEL method to trust in LLMs, providing insights into workplace AI adoption and expanding understanding of trust-building mechanisms.*

Keywords: *Trust in Technology, Large Language Models, DEMATEL.*

JEL Codes: *C44, D83, M15.*

Paper Type: *Research article.*

[1]*Poznan University of Technology, Faculty of Engineering Management, Poland,*
ORCID: 0000-0002-6918-1714, marta.pawlowska-nowak@put.poznan.pl;

1. Introduction

The development of large language models (LLMs), such as GPT-4o, Gemini, and Claude, introduces a new dimension to office work, offering extensive support capabilities in administrative, communication, and decision-making tasks. With their ability to process and generate natural language, LLMs are utilized not only as tools for automating routine tasks but also as analytical support, enabling faster and more accurate data interpretation and even generating recommendations in management processes.

These advanced technologies offer the potential to relieve employees of repetitive tasks, thereby increasing productivity and efficiency by automating routine processes and supporting more complex analyses and interactions. However, for these models to be fully integrated and accepted in workplace environments, building user trust in LLM technology is crucial.

This trust is a key component, as without it, users may be reluctant to adopt LLMs, limiting the scope of their use. Furthermore, user trust affects not only their willingness to use language models but also their readiness to make decisions based on the generated responses.

The issue of trust in the context of AI and LLMs is complex, encompassing concerns related to reliability, data security, and users' understanding of how these technologies operate. Additional concerns arise from privacy issues, the accuracy of generated content, and potential biases embedded in the models. Understanding the factors that influence users' trust in LLMs is essential for the successful implementation of this technology in workplaces.

In office environments, in particular, where decisions based on LLM-provided information can have significant consequences, identifying the determinants of trust becomes critically important. By determining which aspects (such as response credibility, interface accessibility, or users' previous experiences with AI) play the most significant roles, organizations can better adapt their LLM implementation processes and establish conditions that foster technology acceptance.

The integration of LLM technology into workplace environments not only enhances operational efficiency but also supports sustainable development goals (SDGs) by fostering economic growth and reducing inequality (United Nations, 2015). By automating routine tasks, LLMs enable employees to focus on higher-value activities, thereby promoting well-being and productivity (Geels, 2018). Moreover, implementing such technologies in an inclusive manner, with attention to user training and accessibility, aligns with the principles of responsible innovation and social sustainability (Von Schomberg, 2013).

The application of the DEMATEL method in this study confirms its effectiveness in analyzing complex, interrelated factors influencing trust in LLM technology. As highlighted in prior research, DEMATEL provides a structured framework for understanding the causal relationships between determinants, enabling the identification of key factors that significantly impact trust. This method is particularly valuable in contexts where multiple, interdependent variables interact, as it allows for the clear delineation of prominence and influence indicators (Baykasoğlu et al., 2013; Si et al., 2018).

The choice of DEMATEL aligns with the principles of responsible innovation and social sustainability, emphasizing the need for transparent and inclusive methodologies in the evaluation of advanced technologies. The results presented in this study underline the importance of targeted interventions in areas such as user education and accessibility, which are critical for fostering equitable adoption of LLM technologies. By addressing these determinants, organizations can not only improve user trust but also bridge digital divides and support broader sustainability goals.

In light of these considerations, the aim of this article is to identify the determinants of trust in LLM technology among office employees using the DEMATEL method. To achieve this aim, a literature review method was employed to establish an initial catalog of trust determinants for LLM technology among office employees, combined with the multi-criteria relational analysis method DEMATEL.

Following the introduction, the article presents a brief review of the literature on the topic of trust in technology. Next, it describes the procedure used to determine the key determinants of trust in LLM technology among office employees using the DEMATEL method. In the subsequent section, the article presents the results of the original research conducted with a group of office employees who served as experts in the study.

2. Literature Review

The topic of trust in technology, a subject of research for many years, encompasses various dimensions, including trust in information systems, technology adoption within institutions, and the impact of trust on interpersonal interactions in the context of technology (Lankton *et al.*, 2015; Kiran *et al.*, 2010). In the context of this article, the issue of trust in information systems—specifically large language models (LLMs)—takes center stage.

One of the most significant factors influencing trust in LLMs is the models' ability to convey confidence in their responses. Research suggests that employing methods to quantify uncertainty in generated answers can help enhance user trust by providing clearer cues about the quality of responses (Lin *et al.*, 2023). Additionally, mechanisms like self-correction, which enable models to correct their own errors, can be especially valuable for office employees who expect reliable results without needing to personally verify each response (Krishna, 2023).

In terms of trust, it is also crucial that LLMs can recognize their own knowledge limitations, which increases transparency and a sense of accountability in generated responses. Office employees may feel more comfortable using technology that can indicate when it lacks sufficient information or is unsure of its results (Yin *et al.*, 2023).

Privacy and data protection are fundamental to building trust in LLMs, particularly in office environments where employees may have concerns about the security of their data and the information processed by the model. Studies by Plant *et al.* (2022) indicate that more complex models are more vulnerable to data leakage, reinforcing the need for privacy protection technologies (Plant *et al.*, 2022). Employees may be more inclined to trust technology that offers a high level of privacy protection.

Another key factor influencing trust in LLMs is the employees' own understanding of the technology. Research shows that users often have difficulty assessing the accuracy of LLM outputs, which can lead to either excessive trust or, conversely, undue suspicion toward model-generated results (Yin, Vaughan, and Wallach, 2019). Employees who better understand the workings of LLMs are more likely to apply the models' outputs appropriately, maintaining a balanced level of trust.

Trust in LLMs among office employees is also affected by the so-called automation bias, which can lead to over-reliance on LLM-generated results. This issue has been noted in highly automated industries, such as aviation, where responsibility shifts from humans to machines (la Shure, 2023). For office employees, this may manifest as a preference for accepting model responses uncritically, underscoring the need for education and skills development to foster a critical approach to LLM outputs.

The use of LLMs in offices can also lead to increased efficiency, though studies indicate that these effects depend on employees’ acceptance of the technology and their adaptability to new working conditions. Employees open to modern technology and aware of its limitations are more likely to effectively use LLMs while maintaining an appropriate level of trust (Eloundou *et al.*, 2023).

Li, Hess, and Valacich (2008) note that the formation of initial trust in information technology also depends on social norms and the reputation of the organization implementing new technologies, which in office settings may reinforce a positive attitude toward LLMs (Li *et al.*, 2008). Additionally, Gulati, Sousa, and Lamas (2018) point out that factors such as perceived competence and the perceived reciprocity of technology increase trust, supporting its adoption in office work environments. Models incorporating these traits are more accepted by users who see them as reliable tools for supporting daily tasks (Gulati *et al.*, 2018).

Another significant dimension of trust in technology, particularly in LLMs, lies in its intersection with sustainable development. Studies indicate that trust plays a pivotal role in fostering the responsible implementation of AI technologies, which aligns with the broader objectives of sustainable development, such as social inclusivity and environmental responsibility (United Nations, 2015; Von Schomberg, 2013).

For example, transparency and explainability in LLM systems not only enhance trust but also promote responsible consumption of resources (Bocken *et al.*, 2014). Furthermore, user education and accessibility — both critical for building trust — are essential for bridging digital divides and ensuring equitable access to technological advancements (Smith and Anderson, 2018). These elements underscore how trust-building mechanisms in LLMs can support the realization of SDG targets, such as reducing inequalities (SDG 10) and fostering innovation and infrastructure (SDG 9).

In summary, trust in large language models in office settings depends on the consistency between the models' declared and actual performance, organizational support, and the perceived competence of the technology. These factors influence positive perception and readiness to adapt the technology in daily work.

2. Research Methodology

The first step in the proposed method for identifying determinants of trust in LLM technology among office employees involves creating an initial catalog of factors based on a review of the literature. Drawing from the sources cited in the "Literature Review" section, as well as additional sources such as (Liu *et al.*, 2023; Huang *et al.*, 2023; Duan *et al.*, 2023), the following preliminary determinants of trust in LLM technology have been formulated:

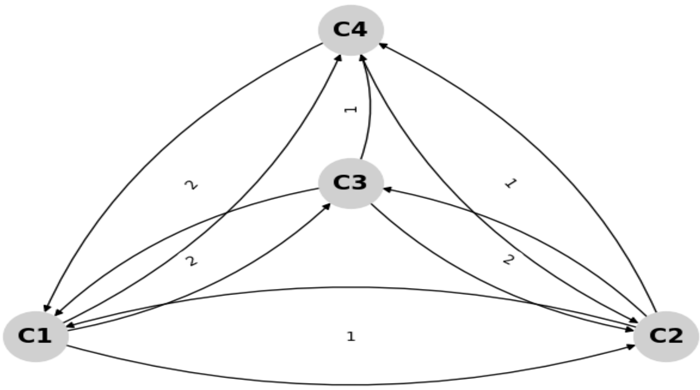
– accuracy and precision of generated responses,
– transparency of operation and algorithm explainability,
– user data security,
– content consistency,
– operational speed,
– high availability and reliability,
– customization to meet user needs and preferences,
– user experience with technology,
– user's educational background,
– user digital skills level,
– prior experience with AI,
– ability to verify sources of generated information,
– compliance with legal regulations,
– alignment of technology values with user values,
– availability of technical support,
– ease of integration with other systems,

– reputation of the technology provider,
– model's ability to maintain neutrality and minimize bias,
– user interface accessibility and intuitiveness,
– auditability and control of results,
– availability of self-education and development tools,
– opinions and recommendations from other users,
– model scalability,
– trust in the model derived from education and training,
– sense of control over outcomes and security,
– cost-value ratio provided by the model,
– clear information on model limitations,
– perceived credibility and truthfulness of generated responses,
– capability for personalization and adjustment of output complexity,
– awareness of the impact on productivity and work efficiency.

This 30-point list was subsequently evaluated by 15 experts, who were office employees of a medium-sized company based in Poznań, Poland, in accordance with the DEMATEL method. The DEMATEL method, as applied to the study of trust determinants in LLM technology, can be represented as a six-step procedure (Si *et al.*, 2018).

Step 1: Development of a Causal-Effect Diagram for Identifying Determinants of Trust in LLM Technology. An example of a causal-effect diagram in the DEMATEL method is shown in Figure 1.

Figure 1. *Example of a Causal-Effect Diagram in the DEMATEL Method*



Source: *Author's elaboration.*

The diagram shows the interrelationships between four elements: c_1, c_2, c_3, and c_4. Each of these elements impacts the others with varying degrees of intensity. The diagram is directional, meaning that arrows indicate the direction of influence from one factor to another. The strength of this influence is represented on a specific scale:

– 0 indicates no connection,
– 1 represents a weak influence,
– 2 represents a strong influence,
– 3 represents a very strong influence.

Step 2: Creation of the Direct Influence Matrix *B*. The direct influence matrix is a numerical (tabular) representation of the relationships between individual factors, which were depicted in the form of a diagram in the first step of the method. The matrix *B*, describing the direct influence of the relationships shown in the diagram, is presented as follows:

$$B = \begin{bmatrix} 0 & 1 & 3 & 2 \\ 1 & 0 & 2 & 1 \\ 2 & 2 & 0 & 1 \\ 2 & 1 & 0 & 0 \end{bmatrix}$$

The main diagonal of matrix B contains only zeros, based on the assumption that no factor influences itself—the analyzed relationships are non-reflexive. For example, the third row of the matrix shows that factor c_3 has a strong influence on factors c_1 and c_2 and exerts a weak influence on factor c_4.

Step 3: Normalization of the Direct Influence Matrix B. In the third stage of the method, the normalization of the direct influence matrix B is performed according to formula (1).

$$BN = \frac{1}{\lambda} B \tag{1}$$

where:

$$\lambda = \max \{\max_j \sum_{i=1}^{n} b_{i,j} ; \max_i \sum_{j=1}^{n} b_{i,j}\} \tag{2}$$

The normalized direct influence matrix, calculated according to formulas (1) and (2) for the considered example, takes the following form:

$$BN = \begin{bmatrix} 0.000 & 0.167 & 0.500 & 0.333 \\ 0.167 & 0.000 & 0.333 & 0.167 \\ 0.333 & 0.333 & 0.000 & 0.167 \\ 0.333 & 0.167 & 0.000 & 0.000 \end{bmatrix}$$

Step 4: Creation of the Total Influence Matrix *T*. The formula defining the total influence matrix *T* is presented as equation (3).

$$T = BN + \hat{B} \tag{3}$$

where: $\hat{B}$ - Indirect Influence Matrix.

The indirect influence matrix $\hat{B}$ is defined using formula (4).

$$\hat{B} = BN^2 + BN^3 + \cdots = \sum_{i=2}^{\infty} BN^i \tag{4}$$

By combining formulas (3) and (4), we obtain formula (5).

$$T = BN + BN^2 + BN^3 + \cdots = \sum_{i=2}^{\infty} BN^i \tag{5}$$

Formula (5) can also be represented as follows (6):

$$T = BN \cdot (I - BN)^{-1} \tag{6}$$

After applying all the described transformations, the total influence matrix T for the considered example takes the following form:

$$T = \begin{bmatrix} 0.894 & 0.895 & 1.245 & 0.988 \\ 0.782 & 0.544 & 0.906 & 0.669 \\ 1.019 & 0.906 & 0.811 & 0.792 \\ 0.762 & 0.556 & 0.566 & 0.441 \end{bmatrix}$$

Step 5: Calculation of Prominence and Relation Indicators. In the DEMATEL method, prominence and relation indicators are calculated using formulas (7) and (8).

$$t_i^+ = \sum_{j=1}^{n} t_{i,j} + \sum_{j=1}^{n} t_{j,i} \tag{7}$$

$$t_i^- = \sum_{j=1}^{n} t_{i,j} - \sum_{j=1}^{n} t_{j,i} \tag{8}$$

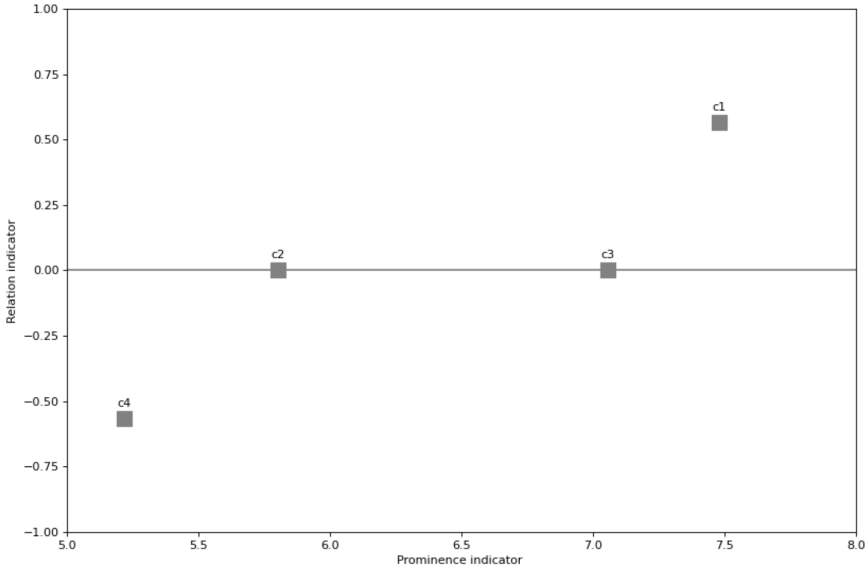
The indicator t_i^+ shows the extent to which a given element contributes to the overall network of relationships among the different components. A higher value of this indicator signals a greater influence of the element on others, as well as the intensity of influences it receives from other elements. In contrast, the indicator t_i^-determines whether an element has a stronger impact on others or is more susceptible to their influence.

For the example under analysis, applying formulas (7) and (8) allows for the determination of the following prominence and relation indicators:

- Prominence indicators t_i^+ : 7.479, 5.801, 7.057, 5.214
- Relation indicators tt_i^-: 0.566, 0.000, 0.000, -0.566

The values of tt_i^+ and t_i^-can then be plotted in Figure 2.

Figure 2. *Prominence-Relation Plot for the Analyzed Example*



Source: *Author's elaboration.*

The analysis of the placement of factors on the chart relates to the concept of influence maps, which are used to visualize and examine relationships among different elements in the analyzed system or problem (Si et al., 2018). Such charts make it possible to determine which factors have a dominant influence on the system, which are strongly interconnected, and which are mainly influenced by others.

The interpretation of each factor's position on the chart is as follows:

- Factors in the upper right part of the chart significantly influence other elements.
- Elements in the central right part of the diagram both strongly impact others and are significantly affected by them.
- Elements in the lower right part of the chart are largely influenced by other factors.
- Factors in the upper left part of the chart show a limited influence on other elements.
- Elements in the middle left part of the diagram weakly influence others and are only slightly affected by them.
- Factors in the lower left part of the chart remain under weak influence from other elements.

The factors in Figure 2 can be interpreted as follows:

- Factor c_1 - located in the upper right part of the chart, indicating that it has a significant impact on other elements. It is the most dominant factor with a positive relation indicator, suggesting its major role in the system.
- Factor c_2 - positioned in the central area along the relation line, meaning that its influence on other elements and the influence it receives are balanced. It is a moderately dominant factor that neither exerts a strong influence on others nor is heavily influenced by them.
- Factor c_3 - similar to c_2, it is located in the central right part of the chart, suggesting a moderate but not distinctly dominant influence. Its position indicates a certain balance between the influence it exerts and the influence it receives.
- Factor c_4 - positioned in the lower left part of the chart, indicating that it is a low-dominance element with a negative relation indicator. This shows a weak influence on other elements and a stronger effect from them. It is the factor most subject to the influence of others, while itself not significantly affecting the system.

Step 6: Determination of Importance Indicators for the Analyzed Factors. The weights for individual factors are determined using formula (9) (Baykasoglu *et al.*, 2013; Dalalah *et al.*, 2011).

$$w_i = \frac{t_i^+ + t_i^-}{\sum_{i=1}^{n}(t_i^+ + t_i^-)} \tag{9}$$

Table 1 summarizes the calculated factor weights according to formula (9).

Table 1. *Weights of Sample Factors*

Factor	c_1	c_2	c_3	c_4
Weight	0.315	0.227	0.276	0.182

Source: *Author's elaboration.*

The analysis of the sample factors highlights their relative significance in the context of trust determinants. Factor **c1**, with the highest weight (0.315), demonstrates its predominant role in influencing the trust network, emphasizing its criticality in designing trust-building strategies. This suggests that addressing the elements linked to **c1** can yield the most significant improvements in trust levels. In contrast, factor **c4**, with the lowest weight (0.182), appears less impactful individually but may contribute indirectly through its connections with other factors. The calculated weights underscore the importance of tailoring strategies to enhance the most influential factors, thereby maximizing the effectiveness of trust-building initiatives.

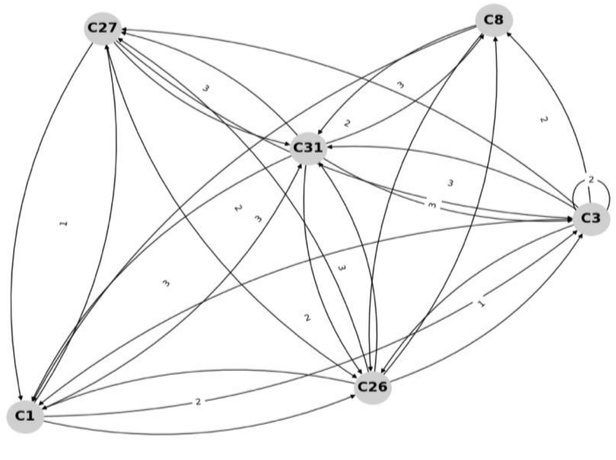
3. Research Results

The survey forming the basis of the presented empirical results was conducted from October 7-11, 2024. Fifteen experts, office employees of a medium-sized enterprise in Poznań, Poland, participated in the study. The experts were selected based on their experience with new technologies, including AI-based technologies, their familiarity with digital tools and related challenges, and their educational background and ability to assess the impact of technology on their daily work. The experts evaluated the mutual influence of trust determinants in technology according to the DEMATEL method procedure. The empirical research results are as follows:

Step 1: Development of a Causal-Effect Diagram for Identifying Determinants of Trust in LLM Technology.

In addressing this issue, a diagram was developed to examine the relationships between 30 potential factors and trust in large language model technology. Due to the numerous edges and vertices, the complete diagram is not fully legible. To illustrate the network of factor relationships, Figure 3 presents a random causal-effect subgraph related to the identification of trust determinants in LLM technology among office employees.

Figure 3. *Subgraph of the Causal-Effect Diagram for Identifying Determinants of Trust in LLM Technology*



Source: *Author's elaboration.*

Step 2: Creation of the Direct Influence Matrix *B*.

The direct influence matrix *B* for the analyzed case has dimensions of 31x31. A portion of the target direct influence matrix is presented as follows:

$$B = \begin{bmatrix} 0 & 2 & 1 & 0 & \cdots \\ 1 & 0 & 2 & 1 & \cdots \\ 2 & 3 & 0 & 2 & \cdots \\ 0 & 2 & 1 & 0 & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix}$$

Step 3: Normalization of the Direct Influence Matrix B.

The normalized influence matrix BN was calculated based on formula (1):

$$BN = \begin{bmatrix} 0.000 & 0.025 & 0.012 & 0.000 & \cdots \\ 0.012 & 0.000 & 0.025 & 0.012 & \cdots \\ 0.025 & 0.038 & 0.000 & 0.025 & \cdots \\ 0.000 & 0.025 & 0.012 & 0.000 & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix}$$

Step 4: Creation of the Total Influence Matrix *T*.
The total influence matrix *T* was determined using formula (6).

$$T = \begin{bmatrix} 0.011 & 0.034 & 0.024 & 0.011 \\ 0.023 & 0.012 & 0.036 & 0.024 \\ 0.044 & 0.055 & 0.044 & 0.043 \\ 0.012 & 0.036 & 0.024 & 0.013 \end{bmatrix}$$

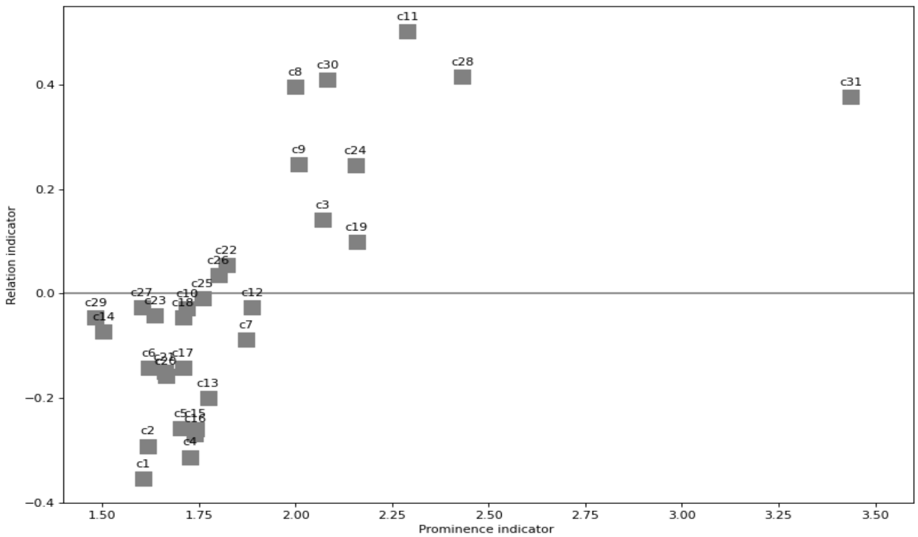
Step 5: Calculation of Prominence and Relation Indicators.
Using formulas (7) and (8), the Relation Indicator and Prominence Indicator were determined:

- Prominence Indicators t_i^+: 1.605, 1.619, 2.069, 1.727, 1.703, 1.620, 1.872, 2.000, 2.009, 1.719, 2.290, 1.888, 1.773, 1.503, 1.741, 1.740, 1.708, 1.708, 2.159, 1.665, 1.662, 1.820, 1.636, 2.155, 1.759, 1.801, 1.602, 2.431, 1.482, 2.083, 3.436

- Relation Indicators t_i^-: -0.355, -0.292, 0.141, -0.313, -0.258, -0.143, -0.087, 0.396, 0.248, -0.028, 0.501, -0.026, -0.199, -0.072, -0.259, -0.268, -0.141, -0.046, 0.100, -0.158, -0.151, 0.055, -0.043, 0.245, -0.009, 0.035, -0.027, 0.415, -0.046, 0.408, 0.377

The values of the indicators t_i^+ and t_i^- are presented in the figure 4.

Figure 4. *Prominence-Relation Chart for Identifying Determinants of Trust in Technology*



Source: *Author's elaboration.*

Step 6: Determination of Importance Indicators for the Analyzed Factors.
Using formula (9), the weights of individual determinants of trust in LLM technology among office employees were calculated. The results are summarized in Table 2.

Table 2. *Importance of Determinants of Trust in LLM Technology Among Office Employees*

C_1	***C_2***	***C_3***	***C_4***	***C_5***	***C_6***	***C_7***	***C_8***	***C_9***	***C_{10}***
0.022	0.023	0.038	0.024	0.025	0.025	0.031	0.041	0.039	0.029
C_{11}	***C_{12}***	***C_{13}***	***C_{14}***	***C_{15}***	***C_{16}***	***C_{17}***	***C_{18}***	***C_{19}***	***C_{20}***
0.048	0.032	0.027	0.025	0.026	0.025	0.027	0.029	0.039	0.026
C_{21}	***C_{22}***	***C_{23}***	***C_{24}***	***C_{25}***	***C_{26}***	***C_{27}***	***C_{28}***	***C_{29}***	***C_{30}***
0.026	0.032	0.027	0.041	0.03	0.032	0.027	0.049	0.025	0.043

Source: *Author's elaboration.*

Among the 10 most important determinants of trust in technology are:

1. Perceived credibility and truthfulness of generated responses (C_{28}) (0.049)
2. Previous experience with AI (C_{11}) (0.048)
3. Awareness of impact on productivity and work efficiency (C_{30}) (0.043)
4. Trust in the model stemming from education and training (C_{24}) (0.041)
5. User experience with technology (C_8) (0.041)
6. Accessibility and intuitiveness of the user interface (C_{19}) (0.039)
7. User educational level (C_9) (0.039)
8. User data security (C_3) (0.038)
9. Opinions and recommendations from other users (C_{22}) (0.032)
10. Ability to verify sources of generated information (C_{12}) (0.032)

4. Discussion

The DEMATEL analysis results point to the key determinants of trust in LLM technology among office employees, which influence their perception and acceptance of this technology. Analyzing factors such as perceived credibility, prior experience with AI, and the intuitiveness of the user interface provides valuable insights into user preferences and concerns, supporting the more effective implementation of technology in office environments.

The most important factor is the perceived credibility of responses generated by LLMs, which received a weight of 0.049. In office settings, the accuracy and truthfulness of information are critical, as any deviation from facts can reduce user trust and increase skepticism towards the technology.

Credibility forms the foundation of trust—without it, employees may view LLMs as an unreliable source of information, limiting their willingness to use the tool regularly.

The second key factor is previous experience with AI (weight 0.048). Individuals with prior positive interactions with AI are more likely to trust LLMs, while negative experiences can foster skepticism. Users with positive AI-related memories may view LLMs as a natural extension of familiar technology, which builds their confidence in the capabilities and reliability of these new models.

Awareness of the impact on productivity (weight 0.043) suggests that employees who see clear efficiency benefits will be more inclined to accept the technology. If users notice that LLMs relieve them of routine tasks or speed up their work, it increases their willingness to use and trust the tool. Training and education (weight 0.041) enhance user confidence in using LLMs, alleviating some of their concerns. Well-trained employees are more likely to understand the limitations and potential of the technology, which increases their trust. Education also helps clarify how AI functions, reducing misconceptions.

User experience (UX) (weight 0.041) influences the positive perception of technology. Intuitive operation and positive UX factors, such as response speed and ease of use, make users more satisfied and therefore more trusting of the technology. An accessible interface (weight 0.039) reduces user apprehension and supports quicker technology adoption. A well-designed, intuitive interface makes it easier for employees to use LLMs and gives them a sense of control over the tool, which translates to greater trust in its functions.

User education level (weight 0.039) influences openness to new technologies—more educated individuals are more likely to accept LLMs and quickly understand its benefits and limitations, which facilitates trust-building. Data security (weight 0.038) is a key aspect in terms of privacy. Concerns about personal data protection can limit trust, so companies must ensure that the technology meets high security standards, giving users confidence that their information is safeguarded.

The opinions and recommendations of other users also impact trust levels (weight 0.032). Employees who hear positive feedback about the technology from their colleagues or peers in similar roles are more likely to trust LLMs. Positive reports from colleagues who successfully use the technology can alleviate concerns and foster a positive attitude toward the new tool. Conversely, negative opinions may have the opposite effect, making it essential for users to have positive initial experiences, which can promote broader acceptance among other employees.

The ability to verify the sources of information generated by LLMs (weight 0.032) is an important factor reinforcing trust in the technology. Users who can verify where generated responses come from or what data they are based on feel more comfortable trusting the system. Such transparency gives users greater confidence that the information they are using is reliable, which may contribute to the broader application of LLM technology in tasks requiring high accuracy.

The findings highlight that trust in LLMs is essential for their adoption, which can be linked to broader sustainability objectives. For example, transparent and ethical deployment of LLMs contributes to social inclusivity by addressing digital divides and promoting equitable access to technology (Smith and Anderson, 2018).

Additionally, optimizing workflows through LLM technology reduces resource consumption, such as time and material waste, which directly aligns with SDG 12 on responsible consumption and production (United Nations, 2015). These impacts demonstrate how trust in AI systems is intertwined with their potential to foster sustainable outcomes.

5. Limitation of the Study

This study has several limitations that should be considered when interpreting its findings. First, the research was conducted among office employees from a single medium-sized company in Poznań, Poland. This specific sample limits the generalizability of the results to other sectors, professional groups, or geographical regions.

Second, the expert assessments were gathered solely from individuals with prior experience in using AI technology. While this focus ensures familiarity with the subject matter, it may introduce biases and overlook perspectives from less technologically experienced users. Expanding the study to include a broader and more diverse participant base would enhance the reliability and applicability of the conclusions.

Future research should investigate how LLM technology directly contributes to sustainable development, particularly in achieving SDG targets such as reducing inequalities (SDG 10) and promoting sustainable industry, innovation, and infrastructure (SDG 9) (United Nations, 2015).

Comparative studies across sectors and geographical regions would provide deeper insights into how trust-building measures in LLM adoption foster long-term sustainable practices. Additionally, exploring the environmental impacts of LLM data processing, such as energy consumption in training models, would provide a balanced perspective on their role in achieving sustainability (Bocken et al., 2014).

6. Conclusions

This study makes a significant contribution to understanding trust in Large Language Model (LLM) technology within office environments, particularly by applying the DEMATEL method to identify and evaluate the key determinants of trust. By focusing on factors such as perceived credibility, prior experiences with AI, data security, and usability, the research highlights the critical elements that influence employees' acceptance and effective use of LLMs.

These findings are particularly relevant for organizations seeking to integrate modern technologies into their management and decision-making processes, offering practical recommendations to enhance user confidence and trust.

The study's emphasis on trust-building mechanisms not only supports technological adoption but also aligns with the broader principles of sustainable development. Incorporating LLMs in office environments can drive efficiency, reduce resource waste, and improve decision-making processes, contributing to the economic and social dimensions of sustainability.

However, the study encourages organizations to adopt these technologies responsibly, ensuring that issues such as transparency, ethical use, and user education are prioritized to mitigate potential risks such as automation bias or misuse of data. By addressing these concerns, companies can foster sustainable technological integration that balances innovation with the well-being of employees and organizational goals.

Future research should explore the intersection of trust determinants and sustainable development more explicitly. This includes examining how LLMs can contribute to achieving broader sustainability objectives, such as reducing environmental impacts through optimized workflows or supporting social inclusion by enhancing accessibility for diverse user groups.

Additionally, comparative studies across different organizational cultures, industries, and geographical regions would offer deeper insights into the dynamics of trust in LLM technology and its role in fostering sustainable development.

Incorporating LLM technology into workplace processes has significant potential to support environmental sustainability. For instance, the automation of administrative and decision-making tasks reduces paper use and lowers the energy demands associated with traditional methods of data processing (Geels, 2018).

Furthermore, LLM systems, when responsibly implemented, can help organizations meet environmental goals by optimizing resource allocation and reducing operational inefficiencies (Bocken et al., 2014). Such applications emphasize the dual benefit of LLMs: improving organizational performance while supporting the global sustainability agenda.

In conclusion, while this research provides valuable insights into the determinants of trust in LLMs, its findings underscore the importance of adopting these technologies with a sustainable and responsible perspective. By integrating trust-building measures with a commitment to sustainable practices, organizations can achieve both technological advancement and long-term positive impacts for stakeholders and the environment.

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