Editorial: Personalized AI communication as a strategic lever for intellectual capital enhancement

Introduction

Advances in artificial intelligence (AI) are enabling an unprecedented degree of personalization in how knowledge is delivered. These advancements can improve communication to audiences and users in widely different contexts, from explaining medical notes to transferring knowledge in educational settings, personalized public announcements, customer service chatbots and more.

Organizations that effectively implement AI-enabled personalized communication strategies can increase their capabilities and grow the value of their human and relational capital. Though the origins of intellectual capital research are grounded in identifying the sources of intrinsic value (the "firm value" of publicly-traded for-profit companies whose market value exceeds their tangible assets), the extensive literature in the *Journal of Intellectual Capital* has shown that the creation and maintenance of intrinsic organizational value can arise from myriad innovative processes and technologies. AI presents a powerful new genesis for growing intellectual value; we anticipate considerable new scholarship in this area that we anticipate publishing in our journal soon!

Systems that incorporate large language models (LLMs) and related generative AI technologies can be designed to configure and curate messages, such as explanations or training content, to fit the unique personal characteristics of individuals along several dimensions. LLMs rely on a rich representation of words in a high-dimensional semantic context (Mikolov *et al.*, 2013). Adapting to the prior knowledge of a student, the emotional state of a patient, the learning preferences of an employee, or even an individual's level of literacy allows a smart system to "meet the users where they are" creating the potential to substantially improve effectiveness, increase user understanding and maintain user engagement. AI-powered systems can move beyond inexact classification of users into predefined audience categories, sensitively identifying characteristics of individual members and then humanely tailoring communications and messaging to each recipient.

Although there are common characteristics governing efficient human communication including, but not limited to, a preference to state given (known) information before stating new information (Haviland and Clark, 1974) and avoiding long-distance structural dependencies (Gibson, 1998), individuals' communication strategies and preferences vary significantly.

Extensive research has established that unique "individual differences" (propensities, dispositions, beliefs, attitudes, etc.) relevant to receptive communication characterize us. Empirically tested theories inform the design of effective messaging to improve adherence to recommended procedures and threat-coping mechanisms. These theories have been applied to achieve various goals including hurricane safety (Sherman-Morris *et al.*, 2015), driving safety (Strawderman *et al.*, 2018) and cybersecurity safety (Johnston *et al.*, 2016). Classically, rhetorical theory organizes the persuasive aspects of communication into three categories–logos (e.g. logic and reason), pathos (e.g. arousing emotions) and ethos (e.g. source credibility). These categories continue to be useful to research that conceptualizes the relationship between individual characteristics and persuasion in messaging.

AI-powered personalization can improve user satisfaction, improve perceptions of messages and increase trust (Florea and Croitoru, 2025; Liu *et al.*, 2025), dimensions that play critical roles in high-stakes settings. Additionally, clearer communication and knowledge transfer can lead to enhanced relationships between the different human parties involved, adding intrinsic value by growing both human capital and relationship capital. To craft

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effective and persuasive messages, modeling who the user is (their traits, context, and level of knowledge) is just as important as modeling the task at hand.

This article will discuss how AI-driven personalization can improve comprehension and reduce confusion across domains and user types. We will also present a novel conceptual model and discuss the challenges, outlook and future directions for utilizing personalized AI explanations in different fields.

The value of personalized communication

The current form of delivering information to end users typically assumes that, as long as we have translated a message into the proper language (internationalization), the target audience will be able to consume the same information equally. However, this one-size-fits-all communication approach often fails to convey complex information to diverse audiences (Johnston *et al.*, 2016). People vary widely in their backgrounds, prior knowledge, experiences, expertise and personalities. The experiences and social roles that a person undertakes also contribute to their differentiated personality development. While individuals are complex, they are also dynamic (Helson *et al.*, 2002; Roberts *et al.*, 2005; Zhu *et al.*, 2024). Even for an individual, characteristics like mood and attentiveness vary over time in ways relevant to receptive communication. Traditional communication approaches struggle to address these individual differences in real-time.

Prior research has applied theories derived from social psychology, communications, and behavioral economics to understand and improve the communication dyad between messenger and message recipient (audience). Scholars have applied theories related to confirmation bias, optimism bias, construal level theory, risk homeostasis dual process theory ("System 1 vs. System 2 thinking"), the elaboration likelihood model, psychological nudges, herd mentality and the endowment effect.

In many scenarios, including healthcare (Rooney *et al.*, 2021), customer service (Følstad and Skjuve, 2019), education (Sharma *et al.*, 2025) and workplace security policy compliance (Johnston *et al.*, 2016) misalignment between message content complexity and user understanding creates a serious communication barrier. As an example, Rooney *et al.* (2021) reported that communication gaps in the context of healthcare contribute to disparities in care. When patients cannot fully comprehend the health information provided to them, they struggle to engage in an informed decision-making process (Rooney *et al.*, 2021). A novice user might get confused by technical language that an expert finds trivial, an anxious patient may need a gentler tone than a calm patient, or a visual learner might prefer diagrams over text. The healthcare professional presenting information to the patient may not understand the patient's personality in a way that would enable them to tailor the medical advice to that particular patient, constraining the patient's understanding and motivation.

AI systems, especially modern LLMs, can address this gap by dynamically tailoring the content and style for each user, making it possible for this personalization to lead to improved audience reception and better outcomes (Florea and Croitoru, 2025; Liu *et al.*, 2025). This capability may be best demonstrated in the context of educational communications, where personalized AI tutors and recommendation systems have shown great promise once they adapt to the unique profile and characteristics of a student. An intelligent system that models differences in prior knowledge, learning pace and motivations can deliver instructions or feedback that is neither too trivial nor too advanced. A recent meta-analysis found that students using AI-driven learning platforms showed greater knowledge retention and engagement than those in traditional settings (Sharma *et al.*, 2025). El-Sabagh (2021) showed that an adaptive e-learning system adjusted to student learning styles was able to deliver significantly higher engagement and performance compared to a non-adaptive system. Likewise, incorporating the personalities of learners and their real-time emotional states into an AI-driven tutoring system made the experience feel more attractive and better aligned with the learner, even improving the learning rate for those students (Fatahi and Moradian, 2018; Favaro *et al.*, 2023). These findings show the effectiveness of mechanisms for tailoring content to individuals in boosting engagement and learning, which support our proposed model.

Experience from the recent wave of AI-powered chatbot design also reinforces the effectiveness of personalization. Studies show that aligning a chatbot persona with user personalities can improve the user experience, resulting in significantly higher satisfaction from the interaction (Følstad and Skjuve, 2019, Helson *et al.*, 2002). An analytical and introverted user might trust a service that adopts a straightforward, detail-oriented style, whereas an expressive user might appreciate a more energetic and personable assistant. Early implementations of AI chatbots in public services have shown improved access to information and services. As an example, Yun *et al*. (2024) report that when people received explanations of government policies that were tuned to the average reading level, they were more likely to read, comprehend and react to those policies. These examples illustrate that AI systems perform best when they account for differences at the individual level to make interactions more engaging, resulting in a better outcome.

Personalization implies forming a concept of the person who plays the audience role in the communication dyad. Here too, AI allows for a rich way to locate an audience member within both the theoretical space of the entire audience and within the temporal space of the users' moment to moment characteristics. This way of modeling users moves beyond crude profiling or a limited number of marketing personas and allows for the nuanced crafting of effective personalized messages. Sometimes referred to as "hyper personalization," the use of AI to move beyond traditional profiling is being vigorously explored in marketing, tourism and customer service research (Morton *et al.*, 2024; Florido-Benítez, 2024). Surely the nuances that attend communication with human patients, students or customers require a similarly rich representation of humans themselves.

Equipped with an accurate picture of the audience, AI can then be applied to the personalization of the message itself. LLMs already exhibit emergent characteristics that enable effective role-playing and customization of communication voice. In addition, new advances in AI training promise that scientific principles emerging from psychological and communications research can inform the creation of comprehensible and persuasive messages. Emerging in the physical sciences, physics-informed neural networks (PINNs) take into account physical laws when learning from real-world data (Raissi *et al.*, 2024). This concept has been extended to sociologically informed neural networks and psychology informed recommender systems (Okawa and Iwata, 2022; Lex *et al.*, 2021). Effective personalization of communication using AI will necessarily involve furthering this work at the intersection of psychology, communications and sociology. In addition, if the content of AI-generated messages includes important factual information, such as medical instructions or dosage guidance, the message customization process will need to be constrained or informed by medical or other sciences.

The core contribution of this model is to illuminate a path by which any system can communicate more effectively through leveraging AI in two ways: first, to build an accurate picture of an audience of one; and second, to craft a message that is truly personalized and informed by coherent psychological principles (e.g. simplifying language for a beginner, adding details and supporting materials for an expert, modulating the tone for someone who is frustrated, appealing to values likely to persuade). This personalization can make information more accessible, reduce cognitive overload or emotional barriers to comprehension, and build user trust and confidence, improvements to elements of communication that form the bulk of the intangible yet critical benefits of any knowledge exchange.

Conceptual model of AI personalization

At a high level, the proposed personalized AI explanation system takes individual user characteristics into account and generates content tailored to those traits, which in turn leads to improved outcomes. The ultimate goal of such a model is to enable the users to grasp the material more easily, so that they will have an improved level of comprehension, reduced confusion or misunderstanding, and increased engagement and satisfaction. In other words, the user receives the right information in the right way.

Figure 1 depicts a personalized AI model. In this model, a *generic message* (1), informed by domain expertise, is first adapted based upon a *user profile* (2), which is curated by embedded AI processes. The user profile places the particular user in a multidimensional context (a "personal embedding") built from feedback on previous interactions with the system, the user's demographic profile or case information, and any formal results from psychometric or other testing. The personal embedding positions the user relative to other users based on dimensions such as their existing level of knowledge, reading level and vocabulary, personality traits and characteristics, rhetorical preferences, learning preferences (such as the preferred delivery format or pace) and other individual differences. In addition to customizing the message for the user's durable profile, the model includes *real-time customization* (3) of the message (which could be an explanation, training materials, advice or instructions) based on analogous cases, the current mood of the user, the necessary tone or degree of formality, or even choosing the right medium (text, audio, visual or a combination of them) based on the user's learning style. The *resulting message* (4) is tailored not only for the subject matter, but for the user and the user's current situation.

The effectiveness of this augmented content should be validated and further adjusted based on the continued interactions between users and the system. These interactions can form a direct or indirect feedback loop as an input to the models involved in components 2 and 3 to improve future content generation. This verification can be performed by a human expert, or alternatively by an agentic AI expert. This will automate the incorporation of user profiles into the model. As the system continues to learn more about users and their preferences, it improves the dynamic vector embedding representation of each user based on their psychological, personal and demographic traits.

Challenges and outlook

Despite the progress and recent advancements in AI, there are still gaps and challenges in current approaches to personal embedding generations and personalized AI. One such limitation is that many systems still rely on relatively coarse or static personalization. Modern personalized AI approaches often suffer from shortcomings in personal embedding generations. Additionally, traditional psychometric-based models and hand-crafted features are unable to fully capture personal traits (Alsini *et al.*, 2024). Alternatively, a small number of static traits might miss the context (e.g. the current mood of the person or situational factors)

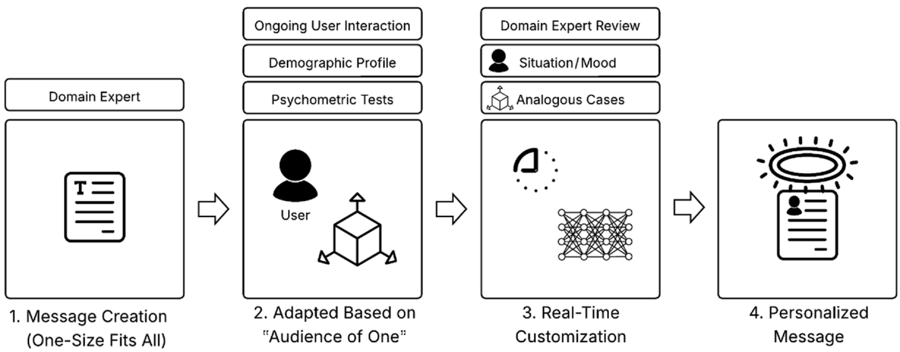

Figure 1. Proposed model for personalized AI explanations

that a truly personalized AI should consider. While incorporating a psychological trait (e.g. the five-factor traits or the Myers–Briggs type indicator) or a demographic profile is a start, it may not capture the full richness of an individual or how their state evolves over time.

Another major challenge is data sparsity. Building an accurate personal embedding requires data about the person, but new users or those who choose not to share information with the system will cause a challenge to these systems (Talha *et al*., 2023). In many real-world cases (e.g. a first-time patient or a new student with few interactions), the model has very limited information to learn from. Multimodal approaches which use different modalities to interact with the user have shown promising results but still require more data to form a generalized model (Ma, 2024).

Moreover, sparse data can lead to unstable or biased embeddings (e.g. overfitting to whatever small quirks are observed). Developing techniques that can personalize with minimal data, perhaps by borrowing insights from populations or using pre-trained persona models, is a potential way of addressing this issue. LLMs have the ability to generate outputs of high quality, but at the same time, one needs to make sure that the generated output is also meaningful, accurate and maintains trust. The model needs an encompassing knowledge base that supplies it with factually accurate information, whether it is through Retrieval Augmented Generation (RAG) or other similar techniques, to ensure alignment of the generated outputs with hard facts. Ensuring that the AI does not hallucinate and disseminate misinformation is critical; personalized nonsense is still nonsense.

The interpretability and trustworthiness of personal AI explanations are other points to consider. By their nature, deep learning embeddings are high-dimensional and not directly human-interpretable; thus, one cannot easily explain what a particular user vector means. In sensitive domains, such as healthcare (Favaro *et al*., 2023) and education, this opacity can be problematic since stakeholders may demand to know why the AI is behaving differently for one user versus another.

Measuring the success of personalization is also non-trivial. It requires user-centered metrics (e.g. comprehension, satisfaction, trust) in addition to traditional accuracy measures. Furthermore, many current benchmarks do not capture these human-centered outcomes, making it harder to quantify progress. As a result, more sophisticated and transparent personalization techniques are required (Liu *et al*., 2025; Ma, 2024), with the goal of moving beyond one-size-fits-all AI.

Future directions

Schools, universities and corporate training departments deploying AI personalization need to consider how it fits into the role of teachers and trainers. As an example, educators can shift from being sole knowledge providers to facilitators or mentors, overseeing AI-tailored learning and intervening when human expertise is needed (e.g. addressing motivational issues or higher-order feedback). However, training and support for instructors on using these AI tools is essential so they trust the system and know how to correct or guide it.

Ensuring that all users feel comfortable using an AI system is another important consideration. Stakeholders must also ensure that personalized AI does not widen the digital divide. In addition to the availability and accessibility of these tools, practitioners must verify that the language and content used by the model are culturally inclusive.

Maintaining oversight of AI-curated content is critical to ensure that the materials generated are accurate and aligned with policies. Additionally, it is important to inform users and administrators alike of the potential benefits of incorporating AI into their existing platforms so that stakeholders accept and adapt to the new system.

Finally, ethical use means protecting users' data, especially when AI is using personal information to adapt and addressing concerns like bias. It is critical to make sure that the adaptations do not inadvertently track to stereotypes (e.g. giving vastly different or easier content only to certain groups).

Conclusion

Personalized AI systems represent a paradigm shift in communication by adjusting messages to intelligible responses, better meeting the needs of each recipient. By tailoring explanations and training content to individual traits, AI can unlock intangible benefits such as clearer understanding, reduced confusion, greater trust, higher engagement and improved outcomes. These benefits result in better and more efficient acceptance of information by the users, which ultimately contributes to the intellectual capital of an organization or society. The concepts and empirical results previously discussed indicate that when people receive information in a way that resonates with them personally, they learn more, they engage more and they feel more empowered. Personalized AI solutions are not solely a technical concept or a technological advancement, but a strategic investment for leaders, managers, and decision-makers that can improve training and communication as a whole, leading to great gains in human capital development.

This promise comes with the responsibility to deploy AI thoughtfully. A human-centered mindset in AI personalization must be executed with care for accuracy, privacy and fairness. The payoff is a more knowledgeable and connected society if we navigate the challenges properly. An AI that can explain a policy to a concerned citizen in plain language, teach a struggling student with appropriate language and patience, guide an employee through new skills at their own pace or comfort a patient with understandable health guidance is not just a tool but rather a catalyst for intellectual growth and mutual understanding. In an age often characterized by information overload and communication gaps, such personalized AI-driven explanations could become a cornerstone of building and sharing knowledge in the years to come.

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