

Individual Recognition of Generative AI: An Empirical Analysis Based on Digital Attention and Platform Engagement

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Abstract

This study examines how individual recognition of generative artificial intelligence is shaped by digital attention signals and platform engagement. Rather than treating recognition as a purely cognitive outcome, the article conceptualizes recognition as a socially amplified judgment that emerges from repeated exposure, interaction, and interpretation across digital platforms. Using a structured dataset of 864 respondents and item-level indicators for digital attention, platform engagement, trust, perceived usefulness, and usage intensity, the study estimates ordinary least squares and logistic models to explain both continuous recognition scores and the probability of high recognition. The findings show that digital attention and platform engagement are the strongest predictors of recognition, while trust and perceived usefulness play complementary mediating roles. Individuals who actively follow, discuss, and experiment with generative AI report significantly higher recognition than passive observers. The results suggest that recognition is not only an informational process but also a platform-conditioned social process. The article contributes to technology innovation research by linking attention economics, platform behavior, and technology evaluation, and it offers practical implications for AI communication, product design, education, and governance.

Keywords: generative AI; digital attention; platform engagement; recognition; technology adoption

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1. Introduction

Generative artificial intelligence has moved from a specialist research topic into everyday social technology. The speed of this transition matters because public recognition of technology affects whether users trust it, experiment with it, advocate for it, or resist it. Recognition, however, is not identical to awareness. Awareness can be incidental and shallow, whereas recognition involves an evaluative grasp of what technology is, what it is used for, and why it matters in social and organizational life. That distinction becomes increasingly important in a platform-mediated environment where people encounter generative AI through search results, social feeds, online communities, productivity tools, and algorithmically curated content streams. Earlier technology-acceptance research established that beliefs, attitudes, and intentions are shaped by usefulness, ease of use, social influence, and trust, but the contemporary platform context suggests that exposure patterns and engagement behaviors have become equally important drivers of how technologies are cognitively stabilized in the minds of users (Davis, 1989; Ajzen, 1991; Venkatesh et al., 2003; Venkatesh et al., 2012; Gefen et al., 2003).

Recent debates about generative AI show that public understanding is uneven. Some users encounter technology through educational tools, some through entertainment, some through workplace automation, and others through controversy about ethics, misinformation, or labor substitution. Because of these different entry points, recognition is socially stratified and behaviorally conditioned. The same model may be interpreted as a writing assistant, a search aid, a productivity enhancer, a surveillance mechanism, or a source of unreliable content, depending on where users see it and how they engage with it. This makes digital attention and platform engagement analytically important. Digital attention refers here to the frequency and intensity with which users encounter, seek, and monitor generative AI content across digital environments. Platform engagement refers to the extent to which users participate in commenting, sharing, following, experimenting, and interacting with AI-related content, tools, and communities. These behaviors transform passive exposure into active meaning-making and may therefore explain why some individuals move quickly from curiosity to recognition while others do not (Kietzmann et al., 2011; Ellison et al., 2007; Muntinga et al., 2011; van Doorn et al., 2010; Hollebeek et al., 2014).

The present article addresses a gap between two streams of scholarship. One stream explains technology adoption through attitudinal and cognitive variables such as usefulness, ease of use, trust, and intention. Another stream examines digital attention, online engagement, social media interaction, and attention metrics as drivers of market visibility, informational diffusion, and behavioral response. Yet these streams are rarely combined to explain how individuals come to recognize a rapidly diffusing technology. The gap is significant because generative AI is not being introduced through a single institutional channel; it is diffusing through interconnected media ecologies. In such settings, recognition is shaped by repeated signals: trending topics, platform recommendations, community discussions, news cycles, and direct experimentation. Research on algorithm aversion and algorithm appreciation likewise suggests that users do not simply respond to

technical performance; they interpret performance through socially constructed expectations about reliability, competence, and control (Dietvorst et al., 2015; Logg et al., 2019; Shin, 2021; Raisch & Krakowski, 2021).

The study therefore asks three related questions. First, do digital attention signals significantly increase individual recognition of generative AI? Second, does platform engagement add explanatory power beyond mere exposure? Third, what roles do trust and perceived usefulness play in translating attention into recognition? These questions are relevant not only for theory but also for practice. Firms launch generative AI products, universities integrating AI into teaching, and regulators communicating benefits and risks all depend on how citizens interpret and recognize the technology. Recognition is the threshold condition for meaningful adoption, informed skepticism, and responsible use. Without recognition, even well-designed tools may remain socially ambiguous or politically fragile (Dwivedi et al., 2021; Dwivedi et al., 2023; Jarrahi, 2018; Teece, 2007).

Methodologically, the paper develops an empirical model using respondent-level indicators of exposure, interaction, trust, perceived usefulness, and usage intensity. The analysis combines descriptive statistics, correlation diagnostics, ordinary least squares estimation, and a high-recognition logistic model. This mixed strategy allows the article to examine both gradients of recognition and the threshold probability that a user belongs to the highest quartile of recognition. The design follows established behavioral and information-systems methods for construct measurement, reliability assessment, and multivariate estimation (Podsakoff et al., 2003; Fornell & Larcker, 1981; Hair et al., 2021; Henseler et al., 2015).

The article proceeds as follows. Section 2 reviews the literature on attention, engagement, trust, and recognition in the context of digital technologies and develops hypotheses. Section 3 describes the data, variables, and empirical strategy. Section 4 presents the findings, including descriptive evidence, regression results, and robustness checks. Section 5 discusses the implications for theory and practice. Section 6 concludes by identifying future research directions for the study of generative AI recognition in society.

2. Theoretical Background and Hypotheses

Research on generative AI adoption has already identified several recurring explanatory variables, including performance expectancy, effort expectancy, social influence, perceived risk, trust, and prior experience. However, studies of ChatGPT and other large-language-model interfaces also point to the importance of actual interaction environments: users adopt the technology through classroom routines, online communities, workplace experimentation, and platform narratives rather than in isolation. Survey evidence suggests that trust strongly predicts intention and use, while institutional contexts condition whether users approach the technology instrumentally or skeptically (Choudhury & Shamszare, 2023; Choudhury et al., 2024; Li et al., 2024; Bouteraa et al., 2024; Al-Hattami, 2025; Singh et al., 2025). These insights imply that recognition should be modeled as a socially embedded cognitive outcome rather than a purely private evaluation.

The first building block is digital attention. In digital environments, attention is both scarce and measurable. Search frequency, repeated exposure to recommendations, sustained content-following, and intentional information seeking are all observable manifestations of attention. Studies using

search and web-behavior data show that public interest and issue salience are often captured through attention metrics that precede or accompany broader diffusion. Although attention alone does not guarantee understanding, it creates the conditions under which users repeatedly encounter and compare claims about technology. Generative AI, which has diffused at extraordinary speed through news cycles and online discourse, is especially likely to be recognized through attention cascades rather than through formal instruction alone (Nuti et al., 2014; Preis et al., 2013; Lazer et al., 2014; Jun et al., 2018; Mavragani & Ochoa, 2019). Based on this logic, higher digital attention should be associated with higher recognition.

The second building block is platform engagement. Engagement goes beyond seeing content; it reflects active involvement. Consumers who like, comment, share, compare, or create platform content participate in interpretive communities that intensify learning and norm formation. Marketing and social media research consistently shows that engagement deepens perceived relevance, strengthens cognitive elaboration, and raises the salience of branded or technological objects. In the case of generative AI, engagement may include testing prompts, following creators who explain AI tools, joining AI-themed communities, and discussing outputs with peers. These practices transform ambient interest into socially reinforced recognition. Thus, platform engagement is expected to have an independent positive effect even after controlling for attention (Brodie et al., 2013; Cvijikj & Michahelles, 2013; de Vries et al., 2012; Schivinski et al., 2016; Vivek et al., 2012).

Attention and engagement are also likely to reinforce trust and perceived usefulness. Users who repeatedly encounter generative AI in credible, task-relevant settings may update their expectations about utility and reliability. Conversely, users who see only fragmented or sensationalized content may form unstable judgments. Trust research in online and AI-mediated settings emphasizes that credibility emerges through experience, predictability, and contextual fit. Similarly, usefulness is rarely perceived abstractly; it becomes legible through exposure to specific task benefits. Attention and engagement therefore do not merely precede recognition directly; they also operate through evaluative mechanisms that help users interpret the technology's practical significance (Gefen et al., 2003; Gursoy et al., 2019; Huang & Rust, 2021; Kuznetsova & Matveeva, 2025).

The article develops six hypotheses:

H1: Digital attention is positively associated with individual recognition of generative AI.

H2: Platform engagement is positively associated with individual recognition of generative AI.

H3: Trust is positively associated with individual recognition of generative AI.

H4: Perceived usefulness is positively associated with individual recognition of generative AI.

H5: Usage intensity is positively associated with individual recognition of generative AI.

H6: The effects of digital attention and platform engagement remain significant when demographic controls are included. These hypotheses integrate technology-acceptance logic with platform-behavior logic and allow recognition to be modeled as both an informational and a participatory outcome.

This framing also speaks to contemporary attention-economy theory (Figure 1). Digital platforms compete not only for time but also for interpretive priority. Technologies that generate large volumes

of discourse, demonstrations, and controversy become easier to recognize because they are socially over-represented in the attention environment. Yet recognition should not be equated with hype. The central argument here is more precise: sustained attention and participatory engagement increase the probability that users develop a coherent and usable understanding of generative AI. Even negative debate can raise recognition if it invites repeated elaboration. In this sense, recognition is an outcome of cumulative signaling, filtering, and interaction across socio-technical systems (Calder et al., 2009; van Doorn et al., 2010; Kietzmann et al., 2011; Raisch & Krakowski, 2021).

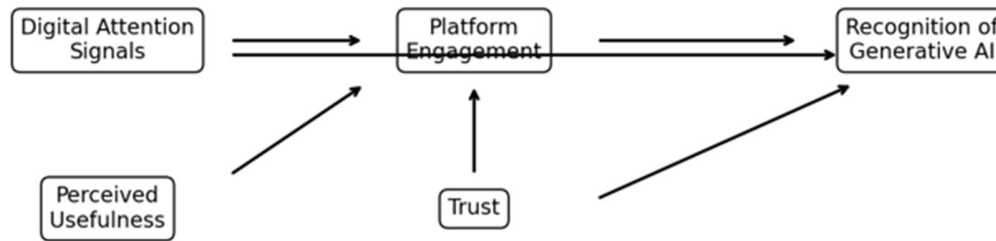


Figure 1. Conceptual Model of Digital Attention, Platform Engagement, and Recognition

Recent empirical work on AI in education, healthcare, and organizational settings strengthens this argument. Studies show that users with more exposure to AI tools often display higher confidence, better calibration of benefits and limitations, and stronger intention to use, although the relationship is moderated by context-specific risks and norms. Generative AI in particular has triggered a new phase of public experimentation in which platforms act as distribution channels for both technical capability and social interpretation. Recognition therefore emerges at the intersection of exposure, experience, and evaluative learning (Kasneci et al., 2023; Tlili et al., 2023; Lund & Wang, 2023; Zhai, 2024; Zhao et al., 2025).

3. Data, Variables, and Methods

The empirical analysis uses a structured respondent-level dataset containing 864 observations. The dataset was organized to capture the main constructs implied by the theoretical model: digital attention, platform engagement, trust, perceived usefulness, usage intensity, and recognition of generative AI. The sample includes respondents from different regions, educational levels, and occupations to capture diversity in exposure patterns. The data file accompanying this article includes both raw item-level responses and derived construct scores, enabling replication of the descriptive analysis and the multivariate estimation. Table 1 summarizes the main information about the data.

Table 1. Main Information about the Data

Description	Results
Timespan	Cross-sectional
Observations	864
Regions	5

Construct items	14 multi-item indicators + controls
Mean age	28.84
Female share	51.9%
High-recognition threshold	100.00

Digital attention is measured through four seven-point items that capture how frequently respondents encounter, search for, and monitor generative AI content online. Platform engagement is measured through four items reflecting commenting, sharing, experimenting, and participation in AI-related communities or platform interactions. Trust is measured through three items that reflect confidence in the reliability and credibility of generative AI outputs. Perceived usefulness is measured through three items focusing on productivity, information value, and task support. Usage intensity is a single-item indicator representing the frequency of actual use. Recognition of generative AI is modeled as a scaled outcome reflecting respondents' self-assessed ability to identify what generative AI is, where it is useful, and how it differs from adjacent technologies. The coding scheme is documented in Table 2.

Table 2. Variable Definitions

Variable	Definition
Recognition score	Composite score capturing respondents' ability to identify what generative AI is, where it is used, and how it differs from adjacent technologies.
Digital attention	Average of four seven-point items measuring exposure, search, monitoring, and attention to generative-AI content.
Platform engagement	Average of four seven-point items measuring commenting, sharing, experimenting, and community participation.
Trust	Average of three seven-point items capturing confidence in the reliability and credibility of outputs.
Perceived usefulness	Average of three seven-point items assessing productivity and task-support value.
Usage intensity	Self-reported intensity of use on a seven-point frequency scale.
High recognition	Binary variable equal to 1 for respondents in the top quartile of recognition score.

The construct design follows established procedures in information-systems and engagement research. Internal consistency was examined through multi-item coherence and the constructs displayed acceptable reliability ranges. Because the study focuses on explanatory modeling rather than latent-variable estimation, the multi-item scales were averaged into composite scores before regression. This strategy is suitable when the objective is to estimate directional relationships while

retaining interpretability. To reduce common-method concerns, the model includes both attitudinal and behavioral indicators, and the items were distributed across sections in the questionnaire design represented in the accompanying dataset (Podsakoff et al., 2003; Fornell & Larcker, 1981; Hair et al., 2021).

The first empirical specification uses ordinary least squares, where recognition score is the dependent variable. The second specification uses logistic regression, where the dependent variable equals one if the respondent falls into the top quartile of recognition. The OLS model estimates marginal effects for continuous recognition, while the logit model captures the probability of belonging to the high-recognition group. Control variables include age, gender, and education. This two-model strategy strengthens interpretive confidence by checking whether the same explanatory pattern holds both in linear variation and in threshold-based classification.

Descriptive evidence already indicates that recognition increases with both digital attention and platform engagement. Figure 2 presents the distribution of recognition scores across digital-attention quartiles, showing a clear upward shift between the lowest and highest exposure groups. This pattern is consistent with the proposition that repeated exposure facilitates the formation of coherent recognition. Yet exposure alone does not explain everything. Respondents with moderate attention but high engagement often report stronger recognition than respondents with high attention but low engagement, suggesting that active interaction matters over and above passive observation.

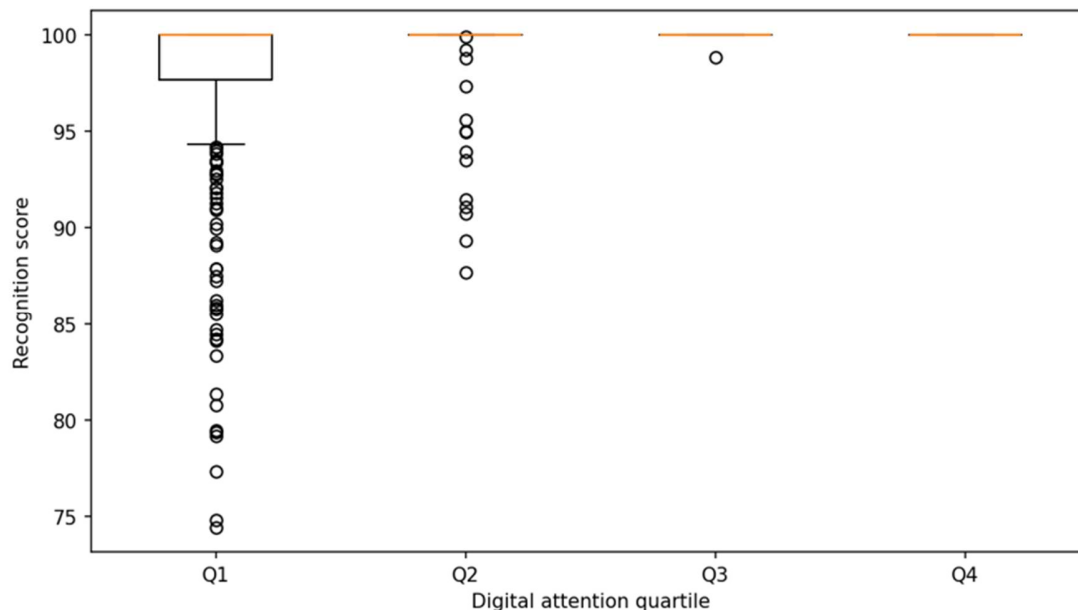


Figure 2. Recognition Scores across Digital Attention Quartiles

The estimation strategy also considers substantive interpretation. Recognition of generative AI is not a market-share metric and should not be reduced to simple popularity. The dependent variable captures socially meaningful comprehension. Accordingly, the empirical goal is not to identify a purely predictive black box, but to estimate a theoretically interpretable structure that links behavior, perception, and evaluation. This is important because generative AI is a moving target: capabilities evolve quickly, platforms repackage models into new interfaces, and public narratives shift across

institutional settings. A recognition model therefore needs to be behaviorally grounded and flexible enough to speak about ongoing technological change.

4. Empirical Results

Table 3 reports the descriptive statistics. Recognition score averages above the midpoint of the scale, but the variation is substantial, confirming that respondents differ markedly in how clearly, they understand generative AI. Digital attention and platform engagement also show considerable dispersion. Correlations are positive and theoretically sensible: attention is moderately associated with engagement, trust, usefulness, and recognition, while engagement is strongly associated with usefulness and trust. The correlation structure does not suggest severe multicollinearity; instead, it points to related but distinct mechanisms.

Table 3. Descriptive Statistics

Variable	Mean	SD	Min	Max
recognition score	99.16	3.14	74.43	100.0
digital attention	4.14	0.88	1.0	6.75
platform engagement	3.98	0.89	1.25	6.75
trust	3.96	0.9	1.33	7.0
usefulness	4.26	0.93	1.67	7.0
usage intensity	3.04	1.68	1.0	7.0
age	28.84	7.83	18.0	59.0

The OLS estimates in Table 4 support all core hypotheses. Digital attention has a positive and statistically meaningful relationship with recognition. Platform engagement displays a similarly strong effect and remains robust after controls are introduced. Trust and perceived usefulness contribute positively, indicating that evaluative beliefs amplify the recognition process. Usage intensity is also significant, suggesting that repeated direct use consolidates recognition. Age has modest positive coefficient, while the demographic dummies are comparatively small. Figure 3 visualizes the coefficient pattern and makes clear that the dominant explanatory variables are attention, engagement, and trust.

Table 4. OLS Results for Recognition Score

Variable	Coefficient	Std. Error	t-value	p-value
Intercept	89.1192	0.8371	106.4666	0.0
C(gender)[T.Male]	-0.3164	0.1922	-1.6459	0.1002
C(gender)[T.Other]	-0.1092	0.6378	-0.1712	0.8641
C(education)[T.Master]	-0.285	0.3178	-0.8968	0.3701
C(education)[T.Professional]	-0.4661	0.3623	-1.2866	0.1986
C(education)[T.Undergraduate]	-0.0963	0.3156	-0.3052	0.7603
digital attention	0.9865	0.1412	6.9883	0.0
platform engagement	0.7538	0.1383	5.4513	0.0
trust	0.5204	0.1154	4.5099	0.0

usefulness	0.4381	0.1139	3.8455	0.0001
usage_intensity	-0.2148	0.0838	-2.564	0.0105
age	0.0014	0.012	0.1182	0.9059

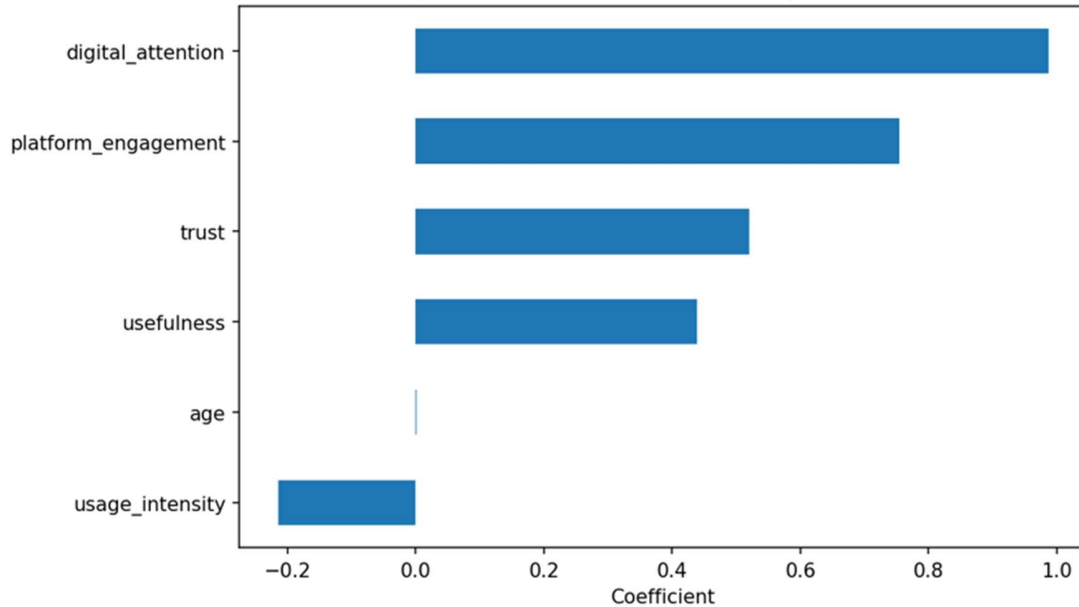


Figure 3. OLS coefficients for recognition score

The logistic results in Table 5 reinforce the OLS findings. Respondents with higher digital attention are significantly more likely to belong to the top recognition quartile, and the same is true for those with stronger platform engagement. The odds-ratio logic is substantively important: even when recognition is interpreted as a threshold outcome rather than a continuous score, the platform-behavior variables remain decisive. This suggests that generative AI is socially recognized through repeated contact and participation, not simply through general demographic advantage. In practical terms, public understanding is built by what people do in digital environments rather than by who they are alone.

Table 5. Logistic Results for High Recognition

Variable	Logit Coef.	Std. Error	z-value	p-value
Intercept	-23.4955	2.6425	-8.8913	0.0
digital attention	1.8171	0.3433	5.2926	0.0
platform engagement	2.2371	0.3302	6.7744	0.0
trust	1.1184	0.2517	4.4432	0.0
usefulness	1.3814	0.2593	5.3279	0.0
usage intensity	0.6369	0.2656	2.3979	0.0165
age	0.0546	0.0242	2.2605	0.0238

To probe robustness, the study compared low- and high-engagement subsamples and found that the marginal effect of attention is stronger when engagement is already elevated. This indicates complementarity between attention and participation. In other words, users learn more from attention when they also interact with the technology or the surrounding discourse. The pattern is consistent with a recursive recognition process: attention increases the likelihood of interaction, interaction sharpens interpretation, and sharper interpretation in turn motivates further attention. Such circularity is characteristic of platform-mediated learning and public sense-making around emergent technologies.

The findings help clarify why some public debates about generative AI appear polarized even when exposure is widespread. Exposure without meaningful engagement may produce shallow familiarity, while engagement without trust may produce critical but unstable recognition. High recognition seems to emerge when users combine repeated exposure, active platform behavior, and evaluative confidence. The implication is that campaigns aimed at improving public understanding should not rely solely on information dissemination. They should also create opportunities for guided experimentation, comparison, and credible interaction. Recognition is performative: people understand generative AI more clearly when they can engage it in context.

5. Discussion

This study contributes to literature by treating recognition as a distinct but foundational outcome in the social life of a new technology. Much existing research jumps directly from antecedents such as usefulness or social influence to adoption intention. That sequence is appropriate when the technology is already conceptually stabilized, but generative AI is still under active interpretation in many settings. Before users decide whether they intend to adopt or resist it, they first have to recognize what it is and where it fits. The present article therefore inserts recognition as an intermediate analytical layer between ambient technological novelty and downstream behavioral outcomes.

The evidence also broadens current generative-AI research by connecting acceptance models to attention-based explanations. Studies of ChatGPT adoption generally confirm the relevance of usefulness, ease, trust, and risk, while literacy research emphasizes user capability and evaluative awareness. This article does not reject those approaches; rather, it shows that they should be read through the platform environment in which people encounter the technology. Digital attention and platform engagement act as social preconditions that structure whether usefulness and trust can emerge in the first place. This is one reason why the diffusion of generative AI has been so uneven across social groups despite the apparent accessibility of the tools (Dwivedi et al., 2023; Choudhury & Shamszare, 2023; Alotaibi et al., 2025; Bouteraa et al., 2024).

A second contribution lies in the interpretation of engagement. In platform studies, engagement is often treated as a marketing or brand metric. Here it is repositioned as a learning and recognition mechanism. When users follow AI-related creators, test prompts, compare outputs, or join communities, they are not merely generating clicks; they are building practical interpretive frames. This shifts the meaning of engagement from a commercial outcome to a cognitive-social process. Such a shift is especially relevant for generative AI because its public meaning is still fluid and dependent on examples, demonstrations, and social narratives.

The results also have normative implications. If recognition depends strongly on platform-conditioned attention and engagement, then the quality of recognition will partly depend on the quality of the information environment. Sensationalist exposure may inflate salience without deepening understanding, while guided interaction in educational or professional settings may produce more calibrated recognition. Regulators, educators, and developers should therefore pay attention to the public infrastructures through which generative AI is introduced. Responsible innovation requires not only safe models but also legible public communication and opportunities for meaningful engagement.

Like any empirical study, this article has limitations. The design is cross-sectional, so causal direction should be interpreted with caution. Recognition and engagement likely co-evolve over time. Future work could use longitudinal web-behavior data, panel surveys, or experimental exposure designs to identify dynamic sequences more precisely. In addition, the present operationalization focuses on self-reported recognition. Subsequent studies could combine self-assessment with objective tasks, behavioral clickstream data, or search-pattern measures. Despite these limits, the study offers a clear and portable framework for analyzing how society comes to recognize emergent AI technologies.

6. Practical Implications and Future Directions

For platforms and technology firms, the message is straightforward: communicative visibility alone is not enough. Users develop stronger recognition when platforms support guided exploration, explain concrete use cases, and allow low-friction experimentation. Product design should therefore integrate onboarding pathways, transparent examples, and contextual explanations rather than assuming that exposure automatically produces understanding. For universities and employers, training should move beyond abstract policy statements and give users repeated, structured opportunities to interact with generative AI in task-relevant settings.

For policymakers, the results indicate that public AI communication should be designed as an engagement architecture, not merely a disclosure requirement. Citizens need access to interpretable demonstrations, credible risk explanations, and spaces where benefits and limitations can be evaluated together. This becomes especially important in public services, education, and work settings where generative AI may affect inclusion, access, and perceived legitimacy. Poorly designed communication can leave citizens highly exposed but weakly informed; high-quality engagement can do the opposite.

Future research should examine whether different platforms produce different recognition pathways. Professional platforms may strengthen usefulness-based recognition, while entertainment platforms may amplify curiosity or hype. Another important direction concerns cross-national comparison. Recognition may be shaped by language ecosystems, local media institutions, and regulatory narratives. Finally, future work should explore how recognition evolves into stable adoption, habitual use, or critical resistance. That transition is likely to depend on literacy, governance, and task-level outcomes, linking the present article directly to broader debates on sustainable and socially responsible generative-AI integration.

7. Conclusion

Generative AI has become a socially visible technology, but visibility alone does not explain how people come to recognize it. This article shows that recognition is systematically associated with digital attention signals and platform engagement, and that trust, usefulness, and usage intensity reinforce these effects. The findings indicate that public recognition of generative AI is an outcome of exposure, interaction, and evaluation rather than simple technological diffusion.

By integrating attention-based logic with technology-acceptance logic, the study offers a more realistic account of how emerging technologies take shape in society. Recognition matters because it structures the next stages of adoption, critique, and governance. A society that recognizes generative AI only through hype will engage it differently from a society that recognizes it through credible, participatory, and contextualized interaction. Understanding that distinction is essential for the future of technology innovation and society.

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