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Who Wants to Try AI? Profiling AI Adopters and AI-Trusting Publics in South Korea

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Abstract

The study introduces new approaches that integrate public relations concepts to identify adopters of AI technologies. It seeks to discover novel methods for identifying target groups likely to adopt AI technologies, even in contexts where these technologies are not yet familiar. The study achieves this by employing latent profile analysis, regression, and structural equation modeling using data from a South Korean online panel survey (N = 625). The results identify five distinct public profiles based on their relationship assessments, problem recognition, and general trust in AI: the Cautious, Balanced, Uninterested, Confident, and Enthusiastic. Notably, the Enthusiastic group—characterized by high trust and strong relationships with the service provider—showed the strongest interest in adopting AI, highlighting their potential as key publics for introducing new AI services in business contexts. Additionally, the article contributes to public segmentation theory through the use of the situational theory of problem-solving and enhances the applicability of established public relations frameworks to the evolving field of AI.

Keywords

AI; AI adoption; public relations; organization–public relationship; situational theory of problem-solving

1. Introduction

Throughout history, every civilization has experienced fear in response to new technologies. Such fear can deeply permeate society, slowing the adoption of technological innovations (Orben, 2020). This underlying panic stems from various factors with some scholars tracing it to psychological reactance (Contzen et al., 2021; Feng et al., 2019). People may fear that a single change could trigger a butterfly effect, disrupting various aspects of life. These sweeping changes can make individuals fear losing their stability and threaten their sense of normalcy. Moreover, those who have become accustomed to using a certain technology for a long time may feel burdened by the need to learn new systems, which often requires time, energy, and, sometimes, financial investment. From an economic standpoint, not all users readily embrace new technologies.

Despite these concerns, the structure of capitalism in the information age drives technological innovations. New technologies often directly correlate with business expansion opportunities. In today's globalized and interconnected world, developing technologies that surpass existing capabilities is ongoing. Companies or countries that gain early access to superior technology can dominate entire economic systems, as modern life increasingly depends on information and communication technologies. Therefore, while public resistance to new technologies persists, entities seeking to develop and introduce innovations consistently look for strategies to popularize their technologies and encourage active consumer adoption.

AI is no different from past innovations when it comes to stirring public anxiety. In 2023, OpenAI launched its generative AI platforms like ChatGPT, which quickly raised alarms about machines taking over human jobs. This emergence sparked widespread debate about job markets, industrial structures, and the broader implications for the value of human labor (Farina & Lavazza, 2023). We can attribute these unprecedented societal concerns about AI to various unresolved ethical issues. That is, as AI-based techniques often function as "black boxes," it is difficult to assess whether their algorithms have a critical bias or infringe on privacy. These built-in ethical issues make people more skeptical of AI today than they were with earlier technologies (Mbiazi et al., 2023).

People's subtle but growing anxieties now focus on the possibility of widespread layoffs, impacting administrators, clerks handling routine paperwork, and, ironically, even developers due to AI's fast and accurate programming capabilities (Constantz & Bloomberg, 2024). Given the current public perception of AI as a threat to humanity, businesses introducing new AI-based services must be cautious to avoid potential customer backlash. Businesses can prevent such a situation and enhance competitiveness by identifying which groups are willing to adopt these innovations.

The diffusion of innovations theory (Rogers, 2003) emphasizes the critical role of early adopters in promoting new technologies. This theory posits that early adopters share several key characteristics. For instance, in a meta-analytic review, Ortt et al. (2017) found that early adopters exhibit high levels of enthusiasm toward new technology, including innovativeness, economic motivation, opinion leadership, and a strong desire to communicate. They tend to engage more with technology and have access to useful resources such as prior experience, technical skills, social networks, and relevant knowledge. Businesses can leverage these factors to identify potential pioneers who can help attract more users to the market. While the role of early adopters in innovation diffusion is sometimes unclear (Bianchi et al., 2017) and can vary across different products or services (Frattini et al., 2014), they play a crucial part in spreading information to non-users, aiding in their understanding, awareness, and decision-making.

Scholars frequently turn to the diffusion of innovations theory (Rogers, 2003) when discussing how new technologies gain traction. The theory is particularly useful for tracking macro-level diffusion trends like the S-curve based on how quickly different groups adopt innovation. However, the theory can overemphasize the influence of innovators and early adopters. As previous literature suggests, individuals categorized as innovators or early adopters make up less than 20% of the population (Ortt et al., 2017) and often come from privileged or higher social status backgrounds. With innovative technologies now more accessible to the general population, it becomes crucial to understand who will adopt AI services when introduced by familiar companies.

In today's technological ecosystem, tech companies—such as those in e-commerce, social networking platforms, and telecommunications—actively promote their technological advancements to customers. Since most people rely on communication technologies, they frequently encounter marketing messages from brands they already use. This loyalty-based ecosystem helps encourage users to try new technologies (Prins & Verhoef, 2007).

Within this context, this study identifies segments of the public who are inclined to try new AI services offered by companies they already use. These individuals may not be early adopters or innovators with abundant resources, but they represent a crucial public. Businesses that focus solely on targeting early adopters may overlook the needs and preferences of more typical users. Therefore, expanding the target public to include potential early adopters who differ from the traditional early adopter profile allows companies to reach a broader market.

This study addresses this issue by employing a public relations perspective, focusing on the importance of relationship quality and situational factors. In public relations, researchers often use organization–public relationship (OPR) and problem recognition to classify and profile key publics. Applying these concepts offers new insights into identifying traits that make certain users more likely to adopt AI. In sum, this study applies a public relations perspective to identify the "AI-trusting public." By examining OPR and problem recognition, it explores how trust in the organization and situational motivation shape people's willingness to adopt AI-based services.

The article unfolds in five sections. First, the literature review discusses the current issues surrounding public trust in AI and examines and presents the study's theoretical concepts, including OPR, situational theory of problem-solving (STOPS), and the research questions and hypotheses. Next, the methods section details the study's data collection process and survey items. Then, the results section follows, presenting findings from regression and structural equation modeling (SEM) analyses. Finally, the article concludes with a discussion of the theoretical and practical implications before offering closing remarks.

2. Literature Review

2.1. Trust Issues about AI

A prevailing distrust toward technology is undeniable. Pieters (2011) outlines the rationale behind how individuals develop trust or a sense of reliability toward technology, observing that most new technologies, including AI, often feel like "black boxes." Most people find it difficult to understand how AI works because its algorithms are so complex. Even experts struggle to keep up with the speed at which AI-driven algorithms process, compute, and analyze data. Scholars and experts have voiced growing concern about AI's invasive impact in the workplace (e.g., Hunt, 2023; Roose, 2023).

News media outlets further diffuse and amplify these sentiments through casual reporting (e.g., Kelly, 2024) and political commentary (Orben, 2020). Consequently, the current negative aura surrounding AI technology can appear "extraordinary" (Battista, 2024) or "magical" (Nagy & Neff, 2024). Widespread concerns about AI's impact on human labor resonate widely with experts and the general population, fueling the broader trust issues people feel toward these technologies (Omrani et al., 2022). For businesses promoting AI, this commonly shared apprehension poses significant challenges (Gerlich, 2023).

Researchers have not just observed this anxiety; they have actively explored the issues of transparency and trust in automated AI-based systems. For instance, Langer et al. (2023) found that users showed very little trust in low-level automated systems, and even when they introduced interventions, they made little difference. Similarly, in the UK, a series of recent studies on AI-based virtual humans and job displacement (Gerlich, 2024a, 2024b) revealed that participants felt anxious and deeply concerned about data exploitation and potential consequences professionally and personally. These findings underscore the importance of transparent AI governance. In response, the Ada Lovelace Institute, a UK-based think tank, proposed policy-based solutions to address society's fear of AI in a recent report (Davies & Birtwistle, 2023).

Trust in technology plays a crucial role in the adoption, use, and application of new technologies. When people hesitate to engage with unfamiliar technologies, that fear can grow stronger, even before any firsthand experience. This article does not aim to assess whether AI will ultimately benefit society, nor does it attempt a deep dive into the ethics of AI usage. Instead, we focus on the pressing need to address the public's trust issues with AI technologies in a more concrete and meaningful way.

However, trust is not a simple concept. Lankton et al. (2015) identified two main concepts: "human-like trusting beliefs" and "system-like trusting beliefs." They further categorized these into sub-concepts: Human-like trust beliefs entail integrity, ability, competence, and benevolence—qualities similar to those found in dyadic human relationships; conversely, system-like trust beliefs include reliability, functionality, and helpfulness, which focus more on operational effectiveness. Thus, when people distrust technology, they tend to question its "human-like" traits, especially whether the technology or those who create it actually have their best interests at heart. Mayer et al. (1995, pp. 718–719) describe this form of trust as "the belief that the trustee will want to do good to the trustor, aside from an egocentric profit motive," implying expectations of the technology's non-harmful intentions.

Following this logic, the negative tone surrounding AI today (Frank et al., 2023), amplified by media and experts, can further deepen public suspicion toward emerging AI services. Businesses find themselves up against this wave of skepticism, which can feel overwhelming. The difficulty in solving such a problem within the business may stem from focusing solely on the relationship between technology and users. However, businesses that offer AI-driven services can act as connectors or mediators, enhancing accessibility to AI technologies by drawing on the relationships they've already built with customers over time. For example, Ameen et al. (2021) found that a company's commitment to its customer relationships plays a significant role in how people experience AI-enabled services.

Given this background, we suggest a new direction: Instead of only analyzing general public trust in AI, we should identify specific user groups that are more open to adopting these services. Some people may show interest due to particular situations, like curiosity about a new technology or a broader concern with it. Others may trust the AI services simply because they trust the company offering them. By looking more closely at these groups, we explore new possibilities for encouraging meaningful and responsible adoption of AI technologies.

2.2. Identifying AI-Trusting 'Publics'

There are several useful theoretical frameworks to understand why people adopt novel ideas and technologies. Among them, diffusion of innovations by Rogers (2003) remains one of the most influential. Rogers introduced a framework for identifying early adopters, those who tend to embrace innovations before others. He defined innovation as "an idea, practice, or project that is perceived as new by an individual or other unit of adoption" (Rogers, 2003, p. 12). His theory treats innovation as inclusive, even when no one in a particular community has previously used it; for example, boiling water in a Peruvian village. Scholars have widely applied this framework to understand how new technologies spread, especially as information and communication technologies have rapidly evolved over recent decades.

Building on Rogers' legacy, many researchers have explored what drives individuals to adopt technology early. For example, Son and Han (2011) identified technology readiness—defined as people's propensity to embrace and use new technologies—as a key predictor of adoption and satisfaction. Balkrishan and Joshi (2013) proposed the use–usage model, which considers multiple environmental factors that shape adoption, including factors like prevalence, utility, and proactive attitudes toward technology. Mahardika et al. (2019) examined impediments to adopting new technologies, highlighting distinctions between behavioral intention and behavioral expectation, which vary according to individuals' experience levels with technology.

These studies primarily focus on an individual's propensity or disposition toward adoption. However, the adoption process for new technologies and innovative tech services is more dynamic; it evolves in response to public awareness and how trustworthy people perceive the sources promoting the innovation.

Besides the diffusion of innovations theory, researchers often turn to other well-established theoretical frameworks such as the technology acceptance model (Davis, 1989) and the unified theory of acceptance and use of technology (Venkatesh et al., 2003). Both models elucidate utility-based factors such as ease of use, perceived usefulness, performance expectancy, and effort expectancy. The premise of these two theories is that users are rational decision-makers who aim to maximize benefits while minimizing the psychological or actual costs of adoption behaviors.

2.2.1. OPR

Unlike previous efforts to identify the strategies or tactics of adopters through frameworks like the diffusion of innovation theory, the technology acceptance model, or the unified theory of acceptance and use of technology, this study emphasizes the significance of relational factors, a core element of public relations research. Public relations revolves around building, maintaining, and cultivating relationships with key publics or stakeholders to help organizations reach their goals. Reaching relationship-based goals requires a long-term investment in creating and nurturing relationships with the public, which becomes central to the decision-making process (Grunig & Hunt, 1984).

Public relations strategies can facilitate the adoption of new technologies by leveraging existing relationships, making it easier for the public to accept and engage with these innovations. However, despite the potential for public relations to influence technology adoption, research has largely concentrated on how public relations might innovate through technology (e.g., Panopoulos et al., 2018) rather than how it can help organizations guide the public toward adopting new technologies.

Public relations concepts offer significant potential for helping organizations identify early adopters when launching new tech services. Among these, the OPR measures how the public evaluates an organization's efforts to build and maintain relationships (e.g., Hon & Grunig, 1999; Huang, 2001a), perceived as their assessment of their connection with the organization. In this context, OPR offers a practical advantage: it helps managers identify favorable customers—those more likely to try new products and possibly influence others to do the same.

Public relations research has extensively studied the antecedents and outcomes of strong OPRs. For example, Huang (2001b) identified several strategies that advance OPR, including mediated communication, social activities, two-way dialogue, ethical and symmetrical communication, and interpersonal interaction. Huang also found that OPR can mediate conflict effectively, using strategies like non-confrontational communication and third-party resolution.

Researchers have also looked at the outcomes of OPR in more detail (Cheng, 2018). For instance, Yang (2007) found that a good OPR can positively affect an organization's reputation. Similarly, Kazoleas and Wright (2001) reported that a strong organization–employee relationship can improve employee morale and job satisfaction. Hon (1997) identified 15 recurring themes from expert interviews showing how OPR can improve public relations effectiveness, such as changing public attitudes, perceptions, and behaviors.

This body of research suggests that OPR can significantly influence how people respond to organizations. Therefore, we can reasonably infer that individuals who feel a strong positive connection with an organization will be more open to trying new services from that organization, even when those services involve technologies that might face general skepticism. For example, when people trust an organization, they are more likely to see its offerings as reliable and credible, regardless of general hesitation toward adopting new technologies.

2.2.2. Problem Recognition of STOPS

Another public relations concept that can help identify key adopters who may become champions of new services is the STOPS (Kim & Grunig, 2011). STOPS views members of the public as active communicators and problem solvers in situations they perceive as problematic. When a member of the public begins to recognize a specific issue as a "problem," they become motivated to act. This motivation often drives communication behaviors known as communicative actions for problem-solving.

Three key factors influence this situational motivation: problem recognition, constraint recognition, and involvement recognition. Among these, problem recognition plays a critical role by raising individuals' awareness of an issue and prompting them to conceptualize it as a problem. Grunig (1997) initially defined problem recognition as the moment when people realize that something needs attention and start thinking about how to respond. Later, Kim and Grunig (2011) refined this idea, defining problem recognition as "one's perception that something is missing and that there is no immediately applicable solution to it" (p. 128). Following this logic, without the public's recognition of an issue as a problem, an organization's decisions have minimal impact on the environment or its public. However, once people start framing an issue as a problem, they are more likely to take action and get involved in solving it.

In traditional technology adoption studies, we can draw parallels between problem recognition and how people perceive the prevalence, usefulness, or relevance of new technologies (e.g., Balkrishan & Joshi, 2013). However, problem recognition goes a step further. It reflects how compelled people feel to take an interest in new technology based on their recognition of a related problem. For example, if the public sees current challenges in information technology as urgent problems, that recognition can create a stronger drive to discover new solutions. In contrast, people who do not view tech-related issues as problems are less likely to see value in adopting new and innovative services, such as AI-powered tools. Essentially, how people recognize the issue can significantly shape their openness to new technologies.

3. Research Questions and Hypotheses

Given the research background and literature review, we propose two research questions and four hypotheses. The research questions explore the profiles of individuals more or less likely to adopt new AI services, considering their levels of general trust in AI, their relationship with the current service provider, and their recognition of technology-related problems. The hypotheses predict relationships between relationship metrics, levels of problem recognition, trust in AI services, and adoption intentions. The specific research questions and hypotheses are as follows.

> RQ1: Which members of the public intend to adopt new AI services based on their general trust in AI, their relationship with the current service provider, and their recognition of technology-related problems?
>
> RQ2: Which members of the public express trust in new AI services, considering their general trust in AI, their relationship with the current service provider, and their recognition of technology-related problems?
>
> H1: Higher levels of (a) OPR and (b) technology problem recognition (TPR) will predict stronger intentions to adopt AI services.
>
> H2: Higher levels of (a) OPR and (b) TPR will predict greater trust in AI services.
>
> H3: OPR, TPR, and general trust in AI technologies will interact to influence (a) AI service adoption intention and (b) trust in AI services.
>
> H4: Trust in AI services will mediate the relationship between (a) OPR and AI service adoption intention and (b) TPR and AI service adoption intention.

4. Methods

4.1. Data

One of the major Korean telecommunications operators provided us with a secondary dataset, which Kantar Korea, an independent online panel company, collected with informed consent from all survey participants. In February 2023, Kantar Korea surveyed 625 South Korean respondents using 40 questions focused on customer satisfaction with telecommunications services and AI products.

The demographics of the sample are as follows: The gender distribution was nearly equal, with 49.3% female (n = 308) and 50.7% male (n = 317). The average age of participants was 33.2 years. Over half of the respondents reported a monthly household income between 3 to 7 million Korean Won (approximately USD 2,200–5,200, with an exchange rate of 1 USD = 1,400 KRW; n = 316, 50.6%). Most respondents had a college-level education (n = 435, 73.1%) and lived in Seoul-si or Gyeonggi-do (n = 316, 49.6%).

4.2. Measures

This study measured variables based on previous research using established frameworks from OPR and STOPS (Kim & Grunig, 2011). Respondents rated all survey items on a five-point Likert scale. All variables showed acceptable internal validity, with Cronbach's alpha values exceeding 0.6 and average variance extracted (AVE) values above 0.5 (Ahmad et al., 2016). In addition, to reduce common method variance, we designed the survey to separate predictor and outcome variables clearly and applied techniques to minimize response bias (Eichhorn, 2014). Appendix 1 of the Supplementary File presents the full set of survey items.

We assessed OPR using four items that captured respondents' perceptions of their relationship with their telecommunications provider. An example item is: "I have confidence in the capabilities of Company A" (α = 0.86, AVE = 0.78), rated on a scale from 1 = *strongly disagree* to 5 = *strongly agree*.

We measured TPR with four items that examined respondents' awareness of technology-related issues. For example, "I often think about the lawsuit regarding Operator X's broadband network usage fees" (α = 0.86, AVE = 0.75). Responses ranged on a scale from 1 = *strongly disagree* to 5 = *strongly agree*.

To assess general trust toward AI technologies, we asked questions such as, "With the introduction of AI, society is gradually transitioning into a new era. How do you view the societal changes brought about by artificial intelligence?" The response ratings were from 1 = *very negative view* to 5 = *very positive view*.

We measured the adoption intention of AI services using six items, including: "Would you be willing to use a service that provides messages and gifts to your loved ones on birthdays or anniversaries even after your passing?" (α = 0.87, *AVE* = 0.72; 1 = *very negative*; 5 = *very positive*).

Finally, we evaluated trust toward AI services from telecommunication operator X using seven items, including: "If AI were to replace humans in sports (e.g., managing games and officiating), how much would you trust it?" (α = 0.83, *AVE* = 0.61), rated from 1 = *strongly distrust* to 5 = *strongly trust*.

Table 1 presents the zero-order correlations among the five key variables, reporting average-to-moderate mean values across variables, with the highest mean for OPR ($M = 3.42$) and the lowest for TPR ($M = 2.64$).

Table 1. Zero-order correlations.

	Variables	1	2	3	4	5
1	OPR	1.00				
2	TPR	0.04	1.00			
3	General Trust in AI	0.14***	0.13***	1.00		
4	AI Service Adoption Intention	0.14***	0.29***	0.29***	1.00	
5	Trust Towards AI Services	0.05	0.21***	0.38***	0.38***	1.00
	M	3.42	2.64	3.40	2.94	3.27
	SD	0.81	0.93	0.88	0.86	0.68

Note: *** $p < 0.01$.

5. Results

We used the Stata 18 MP version for latent profile analysis (LPA), regression, and SEM analysis.

5.1. LPA

LPA uses "a categorical latent variable approach that focuses on identifying latent subpopulations based on a certain set of variables" (Spurk et al., 2020, p. 1). This approach benefits research that seeks to identify previously unknown groups within the population. To that end, RQ1 and RQ2 aimed to identify potential adopters of AI services through a public relations lens. We used three latent variables to define public segments: OPR, technological problem recognition, and general trust in AI technologies.

As Table 2 shows, the five-class model (Class 5) emerged as the optimal model. It yielded the lowest values for key model fit indicators: Bayesian information criterion (4,078.4), sample-size adjusted Bayesian information criterion (4,064.1), and a statistically significant Lo–Mendell–Rubin test ($p = 0.00$). Although the six-class model (Class 6) had a slightly lower Akaike information criterion (3,977.1), other indicators supported Class 5 as the most suitable for creating distinctive profiles (Debus et al., 2024). Further, following Occam's razor principle, a long-standing scientific principle that favors simpler explanations over unnecessarily complex ones,

Table 2. LPA model comparison.

Class	N	Log-likelihood	Free parameters	Akaike information criterion	Bayesian information criterion	Sample-size adjusted-Bayesian information criterion	Lo–Mendell–Rubin
2	625	−2,386.367	10	4,792.734	4,837.112	4,822.83	0.000
3	625	−2,381.806	14	4,791.611	4,853.74	4,839.46	0.002
4	625	−2,370.384	18	4,776.767	4,856.647	4,842.36	0.000
5	625	−1,968.392	22	3,980.783	4,078.414	4,064.13	0.000
6	625	−1,962.529	26	3,977.058	4,092.44	4,078.16	0.001

adding more classes beyond five could overcomplicate the model and hinder meaningful interpretation of each group's characteristics.

We then assigned each respondent to one of the five classes based on their highest latent class probability. The results revealed five groups: (a) the Cautious (*n* = 92, 14.7%) had a moderate relationship with their service providers (*M* = 2.47) and moderate recognition of technology issues (*M* = 3.26), but they reported low trust in AI (*M* = 1.86); (b) the Balanced (*n* = 218, 34.8%) showed a good relationship with their service providers (*M* = 3.43), moderate recognition in technological problems (*M* = 2.57), and a moderate level of trust in AI systems (*M* = 3); (c) the Uninterested (*n* = 6, 1%) had low recognition of technology issues (*M* = 1.88), poor relationships with providers (*M* = 1.12), but moderate trust in AI (*M* = 3); (d) the Confident (*n* = 259, 41.4%) reported high trust in AI (*M* = 4), good relationships with providers (*M* = 3.45), and moderate recognition of technology issues (*M* = 2.72); and (e) the Enthusiastic (*n* = 50, 8%) showed very high trust in AI (*M* = 5), strong relationships with their providers (*M* = 3.74), and above-average interest in technology-related issues (*M* = 2.89).

We created these group names solely for interpretive convenience. They do not stereotype or oversimplify individuals in each class. For example, we consider someone "Cautious" only in the specific context of AI adoption or trust, not in broader terms.

See Figure 1 for a visual breakdown of these groups.

Among these groups, the Enthusiastic had the highest average scores for AI service adoption (*M* = 3.71) and trust (*M* = 3.33). In contrast, the Uninterested group showed the lowest scores for adoption (*M* = 2.48) and trust (*M* = 1.94). When comparing these two groups at opposite ends of the spectrum, the Uninterested group had a younger average age (24.5 years) than the Enthusiastic group (32.6 years). Additionally, the Enthusiastic group consisted mostly of men (70%) than women, while the Uninterested group had an equal

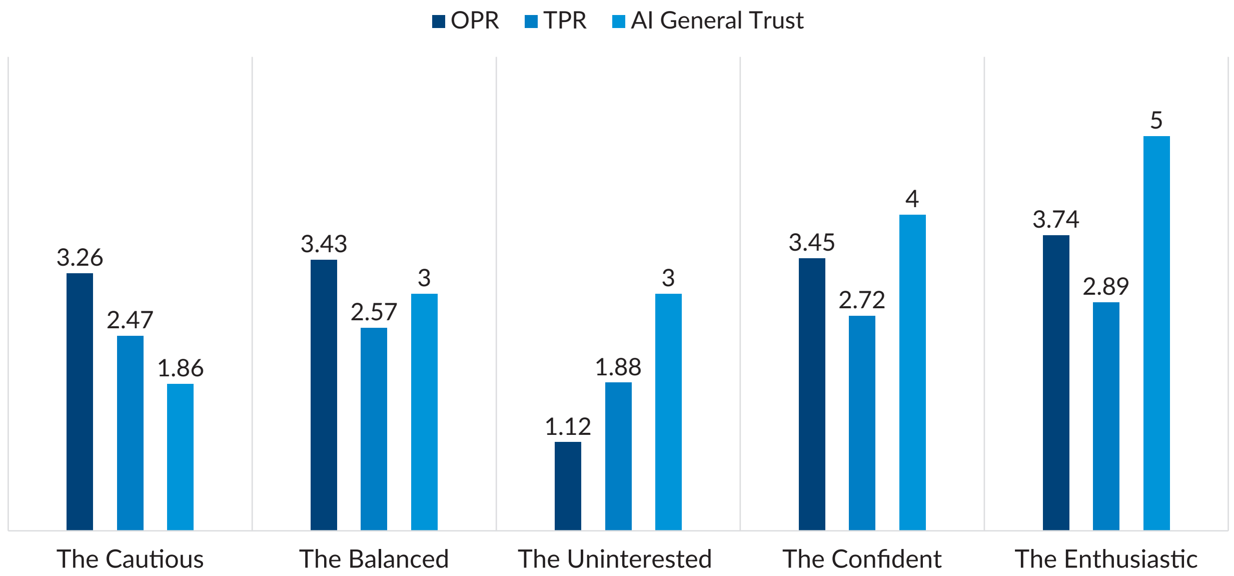

Figure 1. Profiles of OPR, TPR, and AI general trust (on a 5-Likert scale).

gender distribution. Aside from these demographic differences, we found no significant differences in other factors such as household income, education level, or place of residence (RQ1 and RQ2).

Table 3 presents average scores across the five public groups' profiles—the Cautious, Balanced, Uninterested, Confident, and Enthusiastic—based on key variables related to AI adoption.

Table 3. Mean values of variables by profiles.

	Cautious	Balanced	Uninterested	Confident	Enthusiastic
OPR	3.26	3.43	1.12	3.45	3.74
TPR	2.47	2.57	1.88	2.72	2.89
General Trust in AI	1.86	3	3	4	5
AI Service Adoption Intention	2.48	2.87	1.94	3.12	3.37
Trust toward AI Services	2.87	3.11	2.48	3.47	3.71
N	92	218	6	259	50
%	14.7	34.8	1	41.4	8

5.2. Regression Analysis

We tested H1 to H3 using regression analysis to examine the relationships among the key variables. The results show that OPR significantly increased AI service adoption intention ($\beta = 0.44$, $p < 0.01$), supporting H1a. However, OPR did not significantly influence trust in AI services ($\beta = 0.17$, not significant), rejecting H2a.

TPR had no significant effect on service adoption or trust (H1b and H2b). However, when we excluded interaction terms from the model, TPR showed a positive significant effect on AI service adoption ($\beta = 0.28$, $p < 0.001$) and trust in AI services ($\beta = 0.15$, $p < 0.001$).

In contrast, general trust in AI consistently showed stronger effects across both outcomes, positively influencing adoption ($\beta = 0.41$, $p < 0.05$) and trust in services ($\beta = 0.60$, $p < 0.01$).

We also found that those with higher household incomes and younger respondents were more willing to adopt AI services. These findings indicate that general trust in AI plays a more powerful role than situational factors like TPR or the quality of the user–provider relationship when it comes to trusting specific AI services. However, a strong, well-managed relationship with service providers can play a key role in motivating users to try out new technologies.

Table 4 examines the regression results of the predictors of AI service adoption and trust in AI services.

H3 expected interaction effects among the three predictors. We found a significant interaction effect only for AI service adoption ($\beta = -0.44$, $p < 0.05$). The AI adoption probability increased for individuals with lower general trust in AI as their relationship quality with the service provider improved (see Figure 2). This finding suggests that strong relationships with existing customers can play a crucial role in encouraging the adoption of new technologies, even among those who are generally skeptical of AI.

Table 4. Regression analysis results.

	AI Service Adoption		AI Service Trust	
OPR	0.097**	0.438**	−0.001	0.173
	(2.60)	(2.63)	(−0.02)	(1.04)
TPR	0.272***	0.183	0.148***	0.268
	(7.16)	(1)	(3.90)	(1.47)
General Trust in AI (Trust)	0.246***	0.411*	0.352***	0.604***
	(6.58)	(2.29)	(9.46)	(3.38)
Gender (Female = 1)	0.033	0.033	−0.115**	−0.115**
	(0.88)	(0.88)	(−3.07)	(−3.07)
Education Level (University = 1)	−0.043	−0.046	0.003	0.006
	(−1.14)	(−1.23)	(0.08)	(0.16)
Household income	0.095*	0.097**	−0.007	−0.008
	(2.55)	(2.60)	(−0.19)	(−0.21)
Age group	−0.080*	−0.081*	0.002	0.002
	(−2.12)	(−2.17)	(0.07)	(0.06)
Duration of membership	−0.06	−0.048	0.029	0.037
	(−1.62)	(−1.29)	(0.79)	(0.98)
OPR × TPR		−0.012		−0.019
		(−0.71)		(−0.11)
TPR × Trust		0.255		−0.138
		(1.41)		(−0.76)
OPR × Trust		−0.442*		−0.260
		(−1.97)		(−1.16)
N	625	625	625	625
Adjusted R^2	0.171	0.175	0.179	0.178

Notes: Standardized beta coefficients; *t* statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

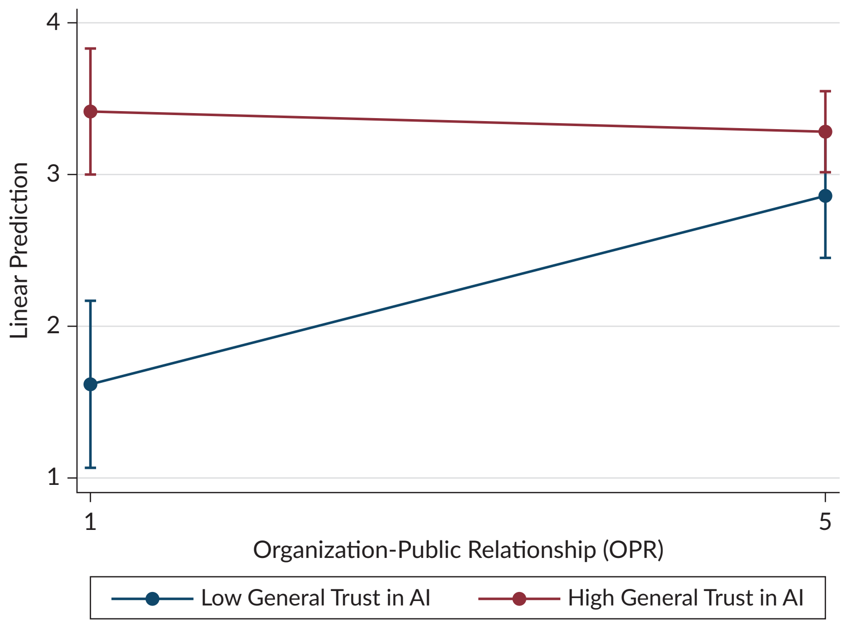

Figure 2. Interaction relationship plots of regression results: AI service adoption.

5.3. SEM

H4 proposed that trust in AI services mediates the relationship between two predictors—OPR and TPR—and AI service adoption. Prior literature emphasized the importance of established trust in AI, suggesting the value of testing its mediating role in this study. We included control variables such as service use duration, age, and income levels to account for their potential influence.

The second-order SEM model (see Figure 3) showed a good fit: $\chi^2(224) = 623.059$, $p < 0.001$, RMSEA = 0.047 [0.042, 0.051], CFI = 0.936, TLI = 0.928, SRMR = 0.066. The results support H4a, showing that TPR indirectly influenced AI service adoption through trust in AI services (TPR—Trust in AI Services: $\beta = 0.23$, $p < 0.001$; Trust in AI Services—AI Service Adoption: $\beta = 0.46$, $p < 0.001$). However, OPR did not significantly influence trust or adoption in this model.

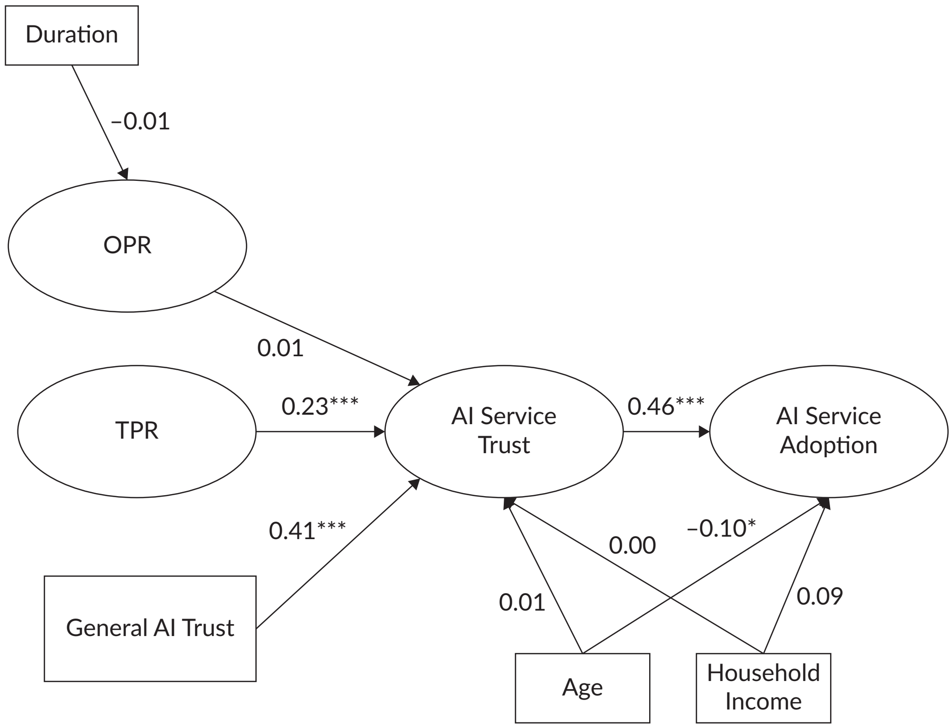

Figure 3. SEM results. Notes: *** $p < 0.001$, * $p < 0.05$; $\chi^2(224) = 623.059$, $p < 0.001$; RMSEA = 0.047 [0.042, 0.051]; CFI = 0.936; TLI = 0.928; SRMR = 0.066.

We also found support for H4b, as general trust in AI significantly influenced adoption intention through its effect on trust in AI services (General Trust—Trust in AI Services: $\beta = 0.41$, $p < 0.001$). All these findings suggest that trust in AI services plays a key mediating role, especially in translating problem recognition and general trust into actual adoption behavior.

6. Discussion

The study introduced a new approach to identifying AI technology adopters by integrating public relations concepts. The study achieved this by using LPA, regression analysis, and SEM. The results identified five public segments' profiles—the Cautious, Balanced, Uninterested, Confident, and Enthusiastic—based on their levels of OPR, recognition of technology problems, and general trust in AI. Among them, the Enthusiastic group stood out, showing the highest levels of AI adoption intent, high trust in AI, and strong relationships with their service providers. This finding suggests that they could serve as the key public group for businesses launching new AI services.

The regression analysis, which tested three hypotheses, revealed that a strong relationship with the service provider positively influenced adoption intention. However, this relationship did not significantly impact trust in specific AI services. Demographic factors such as age and income affected adoption, while education level did not, raising questions about how cognitive factors like education influence AI adoption. We also observed interaction effects: Customers with low general trust in AI were more likely to adopt AI services when they had strong relationships with providers. This finding highlights how relationship-building can drive adoption, even among skeptical users. Strong relational ties can help organizations reduce fear around emerging technologies and shape effective business strategies.

The SEM analysis further revealed that trust in AI services plays a mediating role. Specifically, problem recognition and general trust in AI technologies significantly influenced AI service adoption intention through their effects on service trust. In other words, when people recognize technology-related issues and already trust AI in general, they are more likely to adopt AI services because they trust the service provider.

6.1. Implications for Theory and Practice

The study offers several contributions to theory and practice. First, it expands the application of public relations theory, particularly concepts from OPR and the STOPS, to the field of technology adoption. Unlike conventional approaches, such as the diffusion of innovations theory, which focus on innovators and early adopters with high knowledge or income (e.g., Tran et al., 2024; Uzumcu & Acilmis, 2024), this study highlights the importance of relational factors that apply to a broader range of customers. Communication managers can use these insights to identify strategic publics through relationship metrics, not just demographic or tech-savvy traits.

Second, the findings emphasize the power of long-term relationships. While new service development or market introduction often focuses on new market segments, public relations scholarship stresses the long-term benefits of sustained relationship management. Strong relationships can significantly increase the adoption rate of new services, especially in markets where negative public opinion or skepticism toward AI is prevalent. However, in challenging times such as crises, loyal customers who value their relationship with a company can act as brand advocates, defending the service and its benefits.

Third, focusing on relational factors allows organizations to develop specific adoption strategies. For example, public relations research on OPR has identified several ways to strengthen relationships, such as ethical communication and two-way symmetrical communication. By combining these relationship management strategies with effective marketing and sales efforts, businesses can enhance adoption and increase market share. These strategies are not just for technological companies. Industries like pharmaceuticals, dining services, and retail can also benefit. For instance, a pharmaceutical company launching a new cosmetics line or a restaurant introducing a tech-enabled service system can improve success by understanding and leveraging the relationships they have already built with customers. These relationships are especially important when entering foreign markets, where connected relationships can facilitate the adoption of unfamiliar products or services.

6.2. Limitations and Future Directions

Despite its contributions, the study has some limitations. The most notable is its sample, which includes only Korean participants. Although we controlled for demographic variables, the results may not generalize to other cultures. For example, Koreans may be more open to rapid technological changes compared to consumers in more conservative or risk-averse societies. We recommend future cross-national studies to test external validity in diverse cultural contexts and identify early adopters.

Additionally, while the study employed methods such as LPA, ordinary least squares, and SEM, the one-time survey design limits causal interpretations. The online survey format may also introduce self-selection bias and representativeness issues, which could affect data quality. Therefore, future research should incorporate diverse methods, such as computational analysis, focus groups, in-depth interviews, and experiments, to gain a deeper understanding of how relational and situational recognition factors influence trust in services and adoption behavior. Qualitative methods, in particular, could provide deeper insights into the mechanisms driving these relationships.

Finally, the study relied on OPR and the STOPS. Future research could capture the full scope of relational and situational dynamics by incorporating additional public relations concepts, such as relationship cultivation strategies, communal vs. transactional relationships, and other STOPS variables like involvement recognition, constraint recognition, referent criterion, and situational motivation. Understanding how people perceive tech-related issues could further clarify how they adopt new services.

Beyond academic implications, we must acknowledge the broader social and political uncertainty surrounding AI. Businesses and governments alike face immense pressure as they attempt to regulate and manage AI technologies. Experts continue to debate how best to govern AI at national and international global levels (e.g., UN Global Compact, 2024). As AI begins to reshape market economies, geopolitical competition will increase. For instance, China's DeepSeek has faced allegations of copying AI technologies developed by OpenAI in the US (e.g., Criddle & Olcott, 2025). Meanwhile, the Trump administration 2.0 has reinforced its US-centered and market-driven strategies to maintain American dominance in the AI industry (The White House, 2025).

In this unstable and rapidly evolving context, it is more important than ever to understand how users perceive and adopt AI services. The topic needs more active discussions about how AI will affect users and the relevant strategies for engaging, informing, and building trust with the people who use it.

7. Conclusion

The contemporary era has entered a new phase where society and AI are co-evolving, with technological development expanding at an unprecedented pace. For business leaders and policymakers, this transformation presents challenges, especially in understanding how the public and stakeholders might respond to the ongoing shifts that AI has created. Therefore, it is essential to explore various approaches to understand how the general population adopts AI services.

This study offers novel methods by applying public relations concepts to identify and understand potential adopters of AI technologies. However, while the findings provide meaningful insights, the study also acknowledges its limitations, particularly the limited scope of business sectors and nationalities, which may affect the generalizability of the results. Nonetheless, the study highlights the research potential of various methods for distinguishing potential adopters, contributing to more effective strategies for promoting the adoption of new AI services.

Conflict of Interests

The authors declare no conflict of interests.

Supplementary Material

Supplementary material (appendix) for this article is available online in the format provided by the author (unedited).

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