The Mediating Roles of Satisfaction and Perceived Intelligence In Chatgpt Adoption Among Research and Development Employees: An Extended Technology Acceptance Model

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Abstract.
This study examines how employees in corporate research and development (R&D) units form the intention to use ChatGPT at work, a population that remains underexplored compared with the student samples dominating prior research. Building on an extended Technology Acceptance Model, the study tests whether perceived ease of use, perceived usefulness, and awareness shape behavioural intention to use, with satisfaction and perceived intelligence positioned as dual mediators. Data from 190 R&D employees in Tangerang Regency, Indonesia, obtained through purposive sampling, were analysed using partial least squares structural equation modelling (PLS-SEM). All eight hypothesised direct paths were supported: ease of use and usefulness strengthen satisfaction, awareness builds perceived intelligence, and all five predictors raise behavioural intention, with perceived usefulness as the dominant driver. Perceived intelligence and satisfaction partially transmit the effects of awareness and usefulness, respectively. The findings direct organisations to anchor workplace artificial intelligence adoption strategies in demonstrated usefulness and structured awareness-building.

Keywords: *ChatGPT; Behavioural Intention to Use; Perceived Usefulness; Awareness and Technology Acceptance Model.*

I. INTRODUCTION

Generative artificial intelligence (AI) has moved rapidly from public curiosity to a working instrument embedded in daily organisational routines. Since its release in November 2022, ChatGPT has attracted an exceptionally broad user base and has become the most visible example of conversational AI applied to knowledge work [1]. Its capacity to respond flexibly to varied prompts, contexts, and individual habits makes it attractive for tasks that previously demanded considerable time and cognitive effort [2]. Whether that attractiveness converts into sustained workplace use, however, depends on behavioural intention, the strength of an individual's willingness to employ a particular technology in carrying out tasks [3]. Understanding what builds this intention among employees, rather than among students, is now a practical concern for firms considering how far generative AI should penetrate their operations.

The Technology Acceptance Model (TAM) has long explained adoption through two beliefs, perceived ease of use and perceived usefulness [4]. Recent work on conversational AI argues that these two beliefs are no longer sufficient on their own. Users must first be aware that the tool exists and know what it can and cannot do before rational adoption can begin [2]. In addition, because ChatGPT displays reasoning-like behaviour, users form judgements about how intelligent the system appears, and this perceived intelligence has emerged as a distinct driver of acceptance [2]. Affective evaluation matters as well: satisfaction, the pleasurable fulfilment users feel after interacting with a system, has been shown to carry the influence of instrumental beliefs into continued-use intention [5], [6].

The workplace, moreover, is not simply a larger classroom. Employees answer to performance targets, deadlines, and confidentiality obligations that students do not face, and their evaluation of a new tool is filtered through the question of whether it demonstrably improves the work for which they are accountable. R&D functions sharpen this contrast further: staff in these units routinely draft research reports, analyse experimental data, screen literature, and generate product ideas, precisely the language-intensive and knowledge-intensive activities in which generative AI claims comparative advantage. At the same time, R&D units handle sensitive material, including formulations, technical specifications, and patent-related documents, so their members may weigh the benefits of an external AI service more carefully than casual users. How the classic acceptance beliefs, together with awareness and judgements of machine intelligence,

combine to form usage intention in such an environment is an empirical question that the student-centred literature cannot answer by extrapolation.

Despite this progress, two gaps remain. First, the empirical base is heavily weighted toward students. Influential studies on ChatGPT acceptance drew their samples from universities and schools [2], [5], [6], leaving employees, whose incentives, time pressures, and accountability structures differ substantially from learners, comparatively unexamined. Second, prior models typically test satisfaction or perceived intelligence separately; few combine both as simultaneous mediating mechanisms within a single awareness-extended TAM. This study addresses both gaps by focusing on research and development (R&D) employees in Tangerang Regency, Indonesia, a workforce whose daily tasks, such as experimentation, technical documentation, and idea generation, map naturally onto ChatGPT's capabilities. Although satisfaction is a frequently studied construct, its role here is not as a stand-alone outcome but as one of two parallel mediating channels, alongside perceived intelligence, through which cognitive beliefs and awareness are converted into intention. This configuration, applied to an employee rather than a student population, constitutes the novelty of the paper.

Accordingly, this study aims to test whether perceived ease of use, perceived usefulness, and awareness influence the behavioural intention of R&D employees to use ChatGPT, and whether satisfaction and perceived intelligence mediate those influences. Academically, the paper extends the AI-oriented TAM by demonstrating how cognitive and affective antecedents operate jointly in a workplace setting. Practically, it offers organisations evidence on which levers, usefulness communication, awareness programmes, or user-experience improvement, most effectively encourage productive AI adoption.

Theoretical Review

Technology Acceptance Model

TAM proposes that the decision to adopt an information technology is driven primarily by two beliefs: the extent to which the system is expected to be free of effort, and the extent to which it is expected to improve job performance [4]. Because generative AI introduces properties absent from earlier systems, contemporary studies extend the model with constructs such as awareness and perceived intelligence to capture what users must know and believe about an AI tool before adopting it [2]. This study follows that extension.

Perceived Ease of Use

Perceived ease of use (PEOU) denotes a person's subjective belief that operating a given system will demand little effort [4]. In the ChatGPT context, it reflects how smoothly users expect their interaction with the tool to run, covering the intuitiveness of the interface, the simplicity of navigation, the clarity of instructions, and the effort required to complete a task [7], [8]. The more user-friendly a system appears, the greater the chance an individual will adopt it or keep using it.

Perceived Usefulness

Perceived usefulness (PU) is the degree to which a user believes that a system will raise their job performance [4]. It captures the practical gains, efficiency, productivity, and overall work quality, that users expect from a technology [8]. Within TAM, PU is treated as a core determinant that strongly conditions how individuals evaluate adopting AI tools.

Awareness

Awareness is a key antecedent of technology adoption: before using a tool, individuals must know that it exists, what functions it offers, and what advantages it may bring [2]. For ChatGPT, awareness spans knowledge of its capabilities, applications, and limitations. Individuals with high AI awareness tend to adapt more readily to technology-driven change, whereas those with limited awareness are more likely to feel threatened by it [9].

Satisfaction

Satisfaction is the user's overall affective response after acquiring and using a service, arising from the accumulated sequence of interactions with a system [6]. Applied to conversational AI, it refers to the overall contentment generated through repeated exchanges with a chatbot such as ChatGPT and serves as an indicator of the application's success [5].

Perceived Intelligence

Perceived intelligence (PI) reflects the user's perception of an AI system's cognitive capability and responsiveness, how far it appears able to understand questions, reason logically, and adapt to context [2]. The construct is multidimensional, spanning autonomy, communication ability, logical reasoning, learning capacity, and output quality [10]. When users regard a system as intelligent, their trust in it grows and continued use becomes more likely [11].

Behavioural Intention to Use

Behavioural intention to use (BI) is the subjective probability that a person will employ a technology in the future, encompassing readiness and willingness to use AI tools such as ChatGPT for various purposes [3], [12]. It represents the proximal predictor of actual usage behaviour in acceptance research.

Hypothesis Development

Ease of operation has repeatedly been linked to user contentment in digital settings. When an application demands little effort, interaction proceeds without friction and produces a pleasant experience, which raises satisfaction [13]. Evidence specific to ChatGPT shows that a friendly interface allows users to reach their goals quickly with minimal technical obstacles, thereby increasing their satisfaction [14].

H1: Perceived Ease of Use has a positive effect on Satisfaction.

Perceived benefit is likewise a recognised source of contentment. Users who view an application as capable of optimising their effort place trust in it and evaluate the outcome favourably [13]. For ChatGPT specifically, individuals who judge the tool useful become more motivated and more satisfied with the results they obtain, encouraging continued engagement [5].

H2: Perceived Usefulness has a positive effect on Satisfaction.

Users who hold prior knowledge of what ChatGPT can do are better positioned to judge how intelligently the system understands and answers contextual or technical queries; higher awareness therefore translates into higher perceived intelligence [2], [5]. Familiarity with a chatbot's capabilities also deepens users' appreciation of the intelligence dimensions embedded in it [10], [15].

H3: Awareness has a positive effect on Perceived Intelligence.

Ease of use is among the principal determinants of whether people will take up a new technology: applications judged easy to operate are accepted faster and used more often [16]. When ChatGPT is perceived as effortless, individuals want to incorporate it into daily activities, and well-designed interfaces, clear documentation, and accessible support push usage toward acceptance [2], [5].

H4: Perceived Ease of Use has a positive effect on Behavioural Intention to Use.

Perceived benefit exerts a strong influence on the decision to use an information system, because users adopt technologies that demonstrably improve their performance [17]. Surveys of ChatGPT users confirm a positive disposition toward continued use whenever the tool is seen as helpful, and usefulness emerges as the strongest driver of employees' technology use for completing work [12], [16].

H5: Perceived Usefulness has a positive effect on Behavioural Intention to Use.

As individuals come to understand the benefits and workings of an application such as ChatGPT, they grow comfortable enough to keep using it, and intention rises with the level of awareness [2]. Awareness creates a positive prior belief that the technology is worthwhile, which correlates with stronger adoption intention [5], and employees with superior AI awareness invest more in the competencies that raise their workplace engagement [18].

H6: Awareness has a positive effect on Behavioural Intention to Use.

A fundamental behavioural principle holds that people repeat what satisfies them. Overall satisfaction has consistently been found to strengthen loyalty and continuance intention toward technology [19], and for ChatGPT the cumulative contentment built through repeated interactions inclines users to remain loyal and to use the tool again in the future [5], [6].

H7: Satisfaction has a positive effect on Behavioural Intention to Use.

The more intelligent an AI system appears, the greater the user's trust and the stronger the desire to continue using it [5]. Perceived intelligence builds attitudes and usage intention toward chatbot-based services [20],

and the impression that ChatGPT understands conversational context and adapts to user input turns perceived intelligence into a decisive factor in allocating time and resources to adoption [11], [21].

H8: Perceived Intelligence has a positive effect on Behavioural Intention to Use.

The eight hypotheses form the conceptual framework presented in Fig. 1, in which satisfaction mediates the effects of perceived ease of use and perceived usefulness, while perceived intelligence mediates the effect of awareness on behavioural intention.

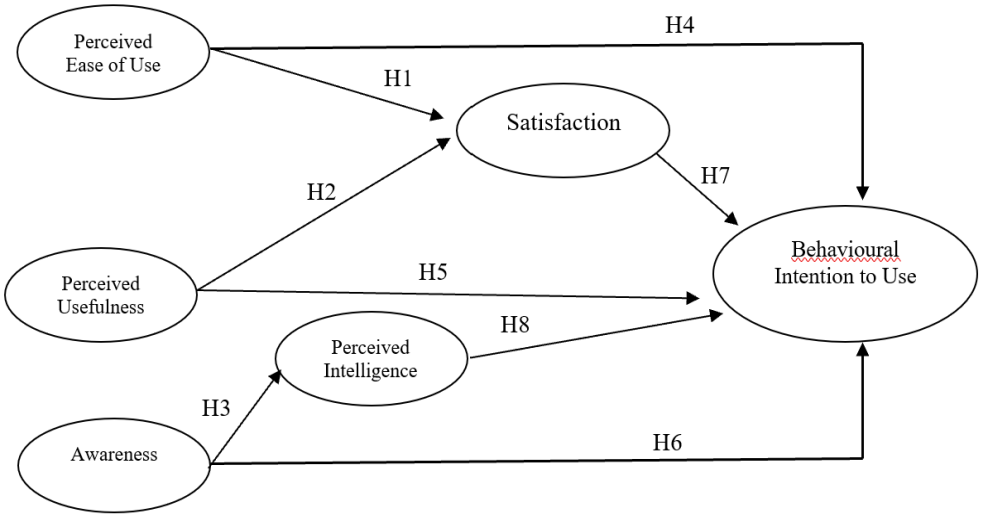


Fig. 1. Conceptual Framework

II. METHODS

This research applied an explanatory quantitative approach with a cross-sectional survey design to test the hypothesised causal relationships among perceived ease of use, perceived usefulness, awareness, satisfaction, perceived intelligence, and behavioural intention to use. Primary data were gathered once, through an online questionnaire administered via Google Forms. The population comprised R&D employees in Tangerang Regency, Indonesia, chosen because their work directly involves technology-supported product development. Purposive sampling was employed with three criteria: aged 18 to 58 years, employed for at least one year, and aware of the existence of ChatGPT. Following the indicator-based guideline of five to ten cases per item [22], the 29-item instrument implied a minimum target of 145 respondents; 190 valid responses were obtained after screening out incomplete or inconsistent answers.

All constructs were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Six PEOU items, five PU items, nine awareness items, and three perceived-intelligence items were adapted from Shahzad et al. [2], while three satisfaction items and three behavioural-intention items were adapted from Yu et al. [6], yielding 29 statements in total.

Data were analysed with partial least squares structural equation modelling (PLS-SEM). The measurement (outer) model was evaluated against outer loadings of at least 0.70, average variance extracted (AVE) of at least 0.50, composite reliability (CR) and Cronbach's alpha of at least 0.70, and discriminant validity using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT below 0.90, or 0.85 for the stricter threshold). The structural (inner) model was assessed through collinearity diagnostics, path coefficients, the coefficient of determination, effect sizes, model fit, and significance testing via bootstrapping [22].

III. RESULT AND DISCUSSION

Respondent Profile

After data screening, 190 valid responses were retained. The gender composition was nearly balanced, and most respondents were of productive working age with higher-education backgrounds and adequate work experience to evaluate ChatGPT use in their jobs. Table 1 summarises the profile.

Table 1. Respondent Profile (n = 190)

Characteristic	Dominant category	n	%
Gender	Male (vs. female: 92; 48.4%)	98	51.6
Age	28-35 years (18-27: 25.8%; 36-48: 28.9%; >=49: 6.8%)	73	38.4
Education	Diploma/Bachelor (high school: 6.3%)	178	93.7
Marital status	Married (single: 35.3%; widowed/divorced: 4.2%)	115	60.5
Job level	Staff (manager: 18.4%; others: 13.7%)	129	67.9
Tenure	1-5 years (6-10: 32.6%; 10-15: 16.3%; >15: 9.5%)	79	41.6

Source: Authors' data analysis (2026)

Measurement Model

Convergent validity and reliability were examined first. Every indicator across the six constructs loaded above 0.70, with the lowest loading at 0.788 (PEOU5), so no item was removed. AVE values ranged from 0.687 to 0.781, Cronbach's alpha from 0.829 to 0.949, and composite reliability from 0.897 to 0.957, all exceeding the required thresholds (Table 2). Discriminant validity was then confirmed by two criteria: all HTMT values fell below 0.85, with the highest at 0.606 for the perceived usefulness-satisfaction pair, and under the Fornell-Larcker criterion the square root of each construct's AVE (0.829 to 0.884) exceeded its correlations with all other constructs. The measurement model was therefore judged valid and reliable.

Table 2. Convergent Validity and Reliability

Construct	Items	Loading range	Alpha	CR	AVE
Perceived Ease of Use	6	0.788-0.885	0.908	0.929	0.687
Perceived Usefulness	5	0.798-0.878	0.899	0.925	0.712
Awareness	9	0.796-0.876	0.949	0.957	0.710
Satisfaction	3	0.865-0.874	0.841	0.904	0.758
Perceived Intelligence	3	0.809-0.893	0.829	0.897	0.744
Behavioural Intention to Use	3	0.879-0.891	0.860	0.915	0.781

Source: Authors' data analysis (2026)

Structural Model

Collinearity was not a concern, as all inner-model variance inflation factor values lay between 1.000 and 1.581, well below the 5.00 ceiling. The model explained 39.8% of the variance in behavioural intention to use (adjusted 38.2%), 32.5% in satisfaction (adjusted 31.7%), and 13.9% in perceived intelligence (adjusted 13.5%); by conventional benchmarks [23] the first two are moderate and the third weak, which is reasonable given that perceived intelligence has a single predictor. Effect-size analysis [24] identified the paths from perceived usefulness to satisfaction and from awareness to perceived intelligence as the medium-sized, most influential relationships, with the remaining paths small (Table 3). Model fit was acceptable: the standardised root mean square residual (SRMR) was 0.064 for the estimated model and 0.053 for the saturated model, both below 0.08 (d_ULS = 1.793; d_G = 0.592; chi-square = 639.030; normed fit index (NFI) = 0.841 for the estimated model).

Table 3. Coefficient of Determination and Effect Sizes

Path / Endogenous construct	R^2 (adj.)	f^2	Category
Satisfaction	0.325 (0.317)	-	Moderate
Perceived Intelligence	0.139 (0.135)	-	Weak
Behavioural Intention to Use	0.398 (0.382)	-	Moderate
Perceived Ease of Use → Satisfaction	-	0.061	Small
Perceived Usefulness → Satisfaction	-	0.240	Medium
Awareness → Perceived Intelligence	-	0.162	Medium
Perceived Ease of Use → Behavioural Intention	-	0.042	Small
Perceived Usefulness → Behavioural Intention	-	0.065	Small
Awareness → Behavioural Intention	-	0.066	Small
Satisfaction → Behavioural Intention	-	0.030	Small
Perceived Intelligence → Behavioural Intention	-	0.035	Small

Source: Authors' data analysis (2026)

Hypothesis Testing

Hypotheses were tested through bootstrapping with 5,000 subsamples, applying $t > 1.96$ and $p < 0.05$ as decision rules. As Table 4 shows, all eight direct hypotheses were supported. The strongest path linked perceived usefulness to satisfaction (0.441), followed by awareness to perceived intelligence (0.373);

among the predictors of behavioural intention, perceived usefulness (0.248) and awareness (0.219) contributed most. The specific indirect effects reveal that awareness influences behavioural intention through perceived intelligence and that perceived usefulness operates through satisfaction, both significant and, since the corresponding direct paths are also significant, both partial mediations. The indirect path from perceived ease of use through satisfaction was not significant, so satisfaction does not mediate that relationship.

Table 4. Hypothesis Testing and Specific Indirect Effects

Path	Coeff.	t-stat.	p	Decision
H1: Perceived Ease of Use → Satisfaction	0.223	3.359	0.001	Supported
H2: Perceived Usefulness → Satisfaction	0.441	7.129	0.000	Supported
H3: Awareness → Perceived Intelligence	0.373	5.808	0.000	Supported
H4: Perceived Ease of Use → Behavioural Intention	0.182	2.724	0.006	Supported
H5: Perceived Usefulness → Behavioural Intention	0.248	3.207	0.001	Supported
H6: Awareness → Behavioural Intention	0.219	3.499	0.000	Supported
H7: Satisfaction → Behavioural Intention	0.163	2.259	0.024	Supported
H8: Perceived Intelligence → Behavioural Intention	0.160	2.377	0.017	Supported
Specific indirect effects				
Awareness → Perceived Intelligence → Behavioural Intention	0.060	2.180	0.029	Significant
Perceived Usefulness → Satisfaction → Behavioural Intention	0.072	2.145	0.032	Significant
Perceived Ease of Use → Satisfaction → Behavioural Intention	0.036	1.751	0.080	Not significant

Source: Authors' data analysis (2026)

Discussion

The support for the first hypothesis indicates that the more effortless R&D employees find ChatGPT, the more satisfied they are with it. Ease here spans access to the platform, comprehension of its instructions, and smooth overall operation without meaningful technical barriers. For employees who navigate ambiguous research-and-development problems daily, a tool that reduces rather than adds cognitive load produces a fluid interaction experience that turns into contentment. This aligns with the finding that a friendly ChatGPT interface lets users reach their goals quickly and with few obstacles, thereby raising satisfaction [14].

The second hypothesis received the strongest support in the model, confirming that tangible benefit is the principal engine of satisfaction. When ChatGPT visibly accelerates task execution, improves report writing and analysis, and supplies innovative ideas, R&D employees judge the system worth using and feel content with its support. Divisions that live on innovation speed and precise documentation reward tools that deliver real productivity gains, which explains why usefulness dominates the formation of satisfaction. The result mirrors evidence that users who perceive ChatGPT as beneficial remain satisfied with their outcomes and are encouraged to continue using it [5].

The third hypothesis demonstrates that awareness builds the impression of machine intelligence. Employees who understand ChatGPT's features, latest versions, and limitations can appraise its capabilities accurately and in the proper context, and that informed appraisal elevates their assessment of its intelligence. Conversely, users with shallow knowledge form misplaced expectations and weaker intelligence perceptions. The pattern is consistent with reports that greater awareness produces a stronger perception that ChatGPT is intelligent [2] and that intelligence dimensions such as reasoning and output quality can only be judged accurately by users with adequate AI literacy [10].

Support for the fourth hypothesis shows that ease of use feeds intention directly, not only through satisfaction. A technology that appears intuitive, requires no lengthy training, and slots into existing processes lowers the resistance that normally blocks new tools at work. Even technically adept R&D employees prefer effortless tools because these let them concentrate on core research problems rather than on operating the software. Comparable studies confirm that applications judged easy to use are adopted more readily [5], [16].

The fifth hypothesis confirms usefulness as the leading direct driver of intention. Rapid report drafting, data analysis, idea generation, and faster literature review constitute utilitarian benefits that make continued use the rational choice for employees under pressure to produce innovative, high-quality output quickly. A tool perceived to deliver fast, relevant, and well-formed responses becomes a strategic asset, and users who see such benefit develop positive intentions toward sustained use [12], [17].

The sixth hypothesis indicates that informed employees are more willing users. Knowing what ChatGPT is, what it can do, and how it develops allows individuals to weigh its relevance to their tasks rationally and to form the belief that it is an innovative, worthwhile technology. Awareness thus acts simultaneously as a knowledge base and as a source of positive predisposition toward adoption, echoing findings that higher awareness of a technology's existence, benefits, and capabilities correlates with stronger adoption intention [2], [5].

The seventh hypothesis affirms the affective route to intention: employees satisfied with ChatGPT's performance, response quality, and overall experience intend to keep using it. Positive experiences predispose people to repeat the behaviour that produced them, whereas disappointment interrupts use. This supports prior evidence that satisfaction significantly shapes continuance intention toward ChatGPT [5], [6].
Finally, the eighth hypothesis establishes perceived intelligence as an independent driver of intention. Willingness to use ChatGPT grows when employees believe the system can answer technical questions, reason through context, and produce output matched to specialised R&D needs. Accuracy alone is insufficient; the system must appear to grasp nuance and adapt its style, which builds the trust that precedes engagement. The result corroborates studies showing that perceived intelligence strengthens attitudes and usage intention toward chatbot services [11], [20].

Mediating Mechanisms

Beyond the direct effects, the mediation results clarify how the model actually works. Awareness does not merely push intention directly; part of its influence travels through the impression of intelligence it creates, meaning that knowledge about ChatGPT first upgrades employees' judgement of the system's capability, which then feeds their willingness to use it. Likewise, usefulness operates partly through the contentment it generates: employees who experience real productivity gains become satisfied, and that satisfaction reinforces their intention beyond the rational calculus of benefit alone. That satisfaction fails to carry the effect of ease of use is itself informative. For a technically fluent R&D workforce, effortless operation appears to be an expected baseline rather than a source of delight, so ease of use shapes intention directly without first passing through an affective response. Both significant mediations are partial, indicating that the cognitive and affective channels operate alongside, not instead of, the direct paths.

Practical Implications

These mechanics translate into practical guidance. Because usefulness is the dominant driver of both satisfaction and intention, organisations should demonstrate concrete, task-level benefits, through case-based training on report drafting, data analysis, and idea generation, rather than promoting the tool in general terms. Because awareness shapes both perceived intelligence and intention, structured literacy programmes, briefings, internal newsletters, and communities of practice that circulate knowledge of features, updates, and limitations, will pay off twice. At the same time, rising adoption in units that handle formulations, technical designs, and patent material must be balanced by governance: standard operating procedures for generative AI use, data-classification and security policies that specify what may never be submitted to public AI platforms, AI-ethics principles that keep human judgement accountable for AI output, capacity building in prompt engineering, and a cross-functional AI-governance framework linking R&D, IT, legal, human resources, and risk management. Adoption managed in this way becomes a durable organisational capability rather than a short-lived enthusiasm, while intellectual property and information security remain protected.

IV. CONCLUSION

This study set out to explain the behavioural intention of R&D employees in Tangerang Regency to use ChatGPT through an awareness-extended TAM with dual mediators. All eight hypotheses were empirically supported: perceived ease of use and perceived usefulness raise satisfaction, awareness builds perceived intelligence, and all five predictors positively shape behavioural intention, with perceived usefulness the most dominant contributor. Perceived intelligence partially mediates the influence of awareness, and satisfaction partially mediates the influence of perceived usefulness, whereas satisfaction does not mediate the effect of perceived ease of use. The extended model accounts for 39.8% of the variance

in behavioural intention, validating the continued relevance of TAM, enriched with awareness and perceived intelligence, for explaining workplace adoption of generative AI.

Several limitations qualify these conclusions. The cross-sectional design captures perceptions at a single point in time and cannot trace how attitudes evolve. The sample is confined to R&D employees in one regency, restricting generalisation to other regions, industries, or occupational groups. The model leaves roughly 60% of intention variance unexplained, suggesting omitted factors such as organisational support, facilitating conditions, social influence, and perceived risk. Self-reported questionnaire data may also carry perception bias.

Future research should therefore adopt longitudinal designs to observe dynamic changes in perception and behaviour, broaden the population across regions, industries, and job types, and incorporate additional variables, including facilitating conditions, social influence, trust, and perceived risk, to reduce unexplained variance. Mixed-method designs combining quantitative modelling with qualitative inquiry would further uncover the motivations, barriers, and subjective experiences that questionnaires cannot capture, strengthening the theoretical account of AI acceptance among employees who actively use these tools.

V. ACKNOWLEDGMENTS

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VI. ETHICAL DISCLOSURE

Prior to completing the questionnaire, respondents received an introductory statement disclosing the researcher's identity and institutional affiliation, the purpose and title of the study, and an explicit assurance that their responses would be used solely for research purposes and would not be disclosed to third parties. Respondents were invited, rather than required, to take part by completing the questionnaire, and no personally identifying information beyond the demographic items reported in this study was collected. A separate written consent form and an explicit statement of the right to withdraw were not included in the questionnaire; this is acknowledged as a procedural limitation for future data collection.

VII. CONFLICT OF INTERESTS

The authors declare no conflict of interest. This research received no external funding, sponsorship, or grant of any kind; it was conducted solely to fulfil the requirements of the corresponding author's master's thesis, and all data were collected independently through the questionnaire described in this study.

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