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Article

Perceived Value and Adoption Intention of Enterprise AI Solutions in Bangladesh: Integrating the Technology Acceptance Model and Diffusion of Innovations Theory

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Abstract

Enterprise artificial intelligence (AI) adoption is increasingly framed as a value-realisation problem rather than a simple question of whether users are willing to try new technologies. This study examines perceived value and adoption intention for enterprise AI/cloud solutions among technology-oriented respondents in Bangladesh by integrating the Technology Acceptance Model (TAM) with Diffusion of Innovations (DOI) theory. Distinct from a conventional predictor-only adoption model, the study specifies a value-realization mechanism in which relative advantage and compatibility shape perceived usefulness, which in turn contributes to adoption intention; direct DOI-to-intention paths are retained to test partial versus full mediation. Innovation adoption readiness is additionally examined as a boundary condition on the usefulness-intention relationship. The supplied database contains 385 complete observations after exclusion of 15 blank rows. Respondents are distributed across students, employed professionals, and self-employed/freelance users, with substantial variation in technology-use frequency and experience. Composite-score path analysis shows that relative advantage and compatibility are positively associated with perceived usefulness ($\beta=.204$ and $\beta=.217$, respectively; both $p<.001$). Perceived usefulness is positively associated with adoption intention ($\beta=.119$, $p=.020$), while relative advantage ($\beta=.147$, $p=.005$), compatibility ($\beta=.156$, $p=.003$), and innovation adoption readiness ($\beta=.150$, $p=.004$) also have significant direct associations with adoption intention. Bootstrap indirect effects through perceived usefulness are positive for both relative advantage ($ab=.025$, 95% CI [.003, .052]) and compatibility ($ab=.026$, 95% CI [.004, .053]). The usefulness $\times$ readiness interaction is not statistically significant ($\beta=.039$, $p=.447$). The findings therefore indicate a partial value-realisation pathway rather than a simple direct-determinants model. The article contributes by linking innovation attributes to the TAM usefulness mechanism in a Bangladesh enterprise-AI context and by showing that readiness operates more clearly as a direct adoption resource than as a moderator of usefulness.

Keywords: IBM AI; enterprise artificial intelligence; perceived usefulness; relative advantage; compatibility; adoption intention; Technology Acceptance Model; Diffusion of Innovations; Bangladesh

1. Introduction

To establish the study context, this subsection moves from the broader organisational significance of artificial intelligence to the specific enterprise-AI setting examined in the study. The

discussion then narrows to IBM AI/cloud solutions and the Bangladesh context, providing the basis for identifying the particular adoption mechanism investigated.

Artificial intelligence (AI) has moved from a specialised computational capability toward a general organisational technology that increasingly participates in analytics, decision support, workflow automation, knowledge work and customer-facing processes. The organisational significance of this transition is not limited to technical performance. AI changes how employees interpret information, how managers allocate work between people and systems, and how organisations convert digital capabilities into operational and strategic value. Contemporary scholarship consequently treats AI as both an information-processing technology and an organisational phenomenon whose consequences depend on the interaction between technical affordances, human judgement and work practices [1]-[4].

For enterprise technology providers, this creates a practical adoption challenge. Demonstrating that an AI solution exists is insufficient if potential users cannot identify a meaningful advantage over existing practices, cannot see how the technology fits their work, or cannot translate perceived usefulness into an intention to adopt. The literature on AI acceptance has repeatedly identified perceived usefulness, performance expectancy, trust and effort expectancy as important correlates of intention, while also showing substantial heterogeneity across technologies and contexts [5]. AI adoption research has therefore increasingly moved beyond generic technology acceptance toward context-sensitive models that explain why a particular innovation becomes meaningful to particular users.

IBM is an especially relevant enterprise-AI context because the research problem concerns AI/cloud solutions used in professional and organisational environments rather than consumer entertainment applications. The supplied questionnaire explicitly operationalises perceived usefulness, relative advantage, compatibility, innovation adoption readiness, performance expectancy, effort expectancy, trust, technology readiness, digital skills readiness and adoption intention. The present article focuses on the subset most directly aligned with the supplied title and the recommended TAM-DOI theoretical framing: relative advantage, compatibility, perceived usefulness, innovation adoption readiness and adoption intention. This selective strategy follows the instruction in the master questionnaire that each student article should analyse only the constructs and hypotheses relevant to its own research problem [6].

The Bangladesh context is important because technology adoption in emerging economies can involve a different combination of organisational constraints, skills development, infrastructure dependence and professional exposure than adoption in mature digital markets. Existing Bangladesh studies have already applied TAM and related acceptance models to ICT and AI, including research involving extension officers and professional users [7], [8]. However, the supplied research plan identifies a narrower problem: there is limited local evidence concerning how IT-oriented users perceive the usefulness, business value and implementation readiness of IBM AI solutions [9]. The present study addresses this problem by modelling perceived value as a process rather than as a single descriptive attitude.

The central research problem is that enterprise AI adoption can be analytically reduced to intention scores without explaining how users arrive at that intention. A high intention-to-adopt score does not by itself reveal whether the underlying driver is a belief that AI is better than existing approaches, a perception that it fits established workflows, an assessment that it improves task performance, or a broader readiness to experiment with innovation. Such distinctions matter because the managerial response differs by mechanism. If perceived usefulness is the central transmission mechanism, organisations should demonstrate task-level value. If compatibility is central, integration and workflow design become more important. If readiness is a direct determinant, professional development and experimentation opportunities may matter more.

The problem is especially consequential for enterprise AI because the value of an AI system is rarely realised at installation. It emerges when users understand what the system can do, perceive a meaningful improvement over existing approaches, integrate the technology into work routines, and

decide to use it. Research on human-AI collaboration similarly emphasises complementarity between computational capabilities and human judgement [10], while organisational AI scholarship notes the tension between automation and augmentation [11]. The adoption decision is therefore simultaneously technological and behavioural.

The supplied master questionnaire offers an unusually useful opportunity to separate these mechanisms because it contains both DOI attributes and TAM-style usefulness measures. Rather than treating all available constructs as interchangeable predictors, this article asks whether innovation attributes first shape usefulness perceptions and whether usefulness subsequently translates into adoption intention. The analysis also tests whether innovation adoption readiness changes that translation. This creates a more distinctive model than a simple direct-effects regression and aligns closely with the theoretical combination specified in the research plan.

With the research problem clarified, this subsection identifies the gaps that the proposed model is designed to address. The discussion distinguishes empirical, theoretical and boundary-condition gaps so that the contribution of the integrated DOI-TAM perspective can be evaluated against clearly defined needs in the literature.

Three gaps motivate the study. First is an empirical gap. Reviews of AI acceptance show that TAM and UTAUT dominate the field, but the evidence remains fragmented across technologies, sectors and user populations [5], [12]. A recent bibliometric review similarly identifies TAM and UTAUT as major themes while noting that AI adoption studies remain concentrated in specific industries and that relationships among individual and technological determinants need further investigation [13]. Bangladesh-specific studies provide useful evidence, but they generally examine broad AI use or particular applications rather than the perceived value of enterprise AI solutions through an integrated DOI-TAM mechanism [7], [8].

Second is a theoretical gap. DOI explains why an innovation is attractive in terms of characteristics such as relative advantage and compatibility, whereas TAM explains how usefulness perceptions relate to behavioural intention [14], [15]. Applying the theories side-by-side can produce a list of predictors, but a more theoretically informative integration treats DOI attributes as antecedents of a TAM usefulness judgement. The resulting model asks whether users first translate innovation characteristics into a task-value belief and then convert that belief into an adoption intention. This is a mechanism-level extension rather than a simple accumulation of variables.

Third is a boundary-condition gap. The supplied questionnaire includes innovation adoption readiness, defined through openness to advanced enterprise technologies, willingness to experiment and the perceived importance of innovation for competitiveness. Readiness can plausibly strengthen adoption, but it is not obvious that readiness changes the extent to which usefulness becomes intention. Testing this interaction allows the study to distinguish between readiness as an independent resource and readiness as a contingency. That distinction is valuable because a non-significant interaction is theoretically informative: it suggests that being ready to innovate may raise intention without fundamentally changing the usefulness-to-intention mechanism.

The general objective is to explain perceived value and adoption intention for IBM AI/cloud solutions among IT-oriented respondents in Bangladesh through an integrated DOI-TAM model.

Specific objectives are: to examine whether relative advantage and compatibility predict perceived usefulness; to determine whether perceived usefulness predicts adoption intention; to test whether relative advantage and compatibility have direct effects on adoption intention after usefulness is controlled; to assess whether perceived usefulness mediates the relationships between DOI attributes and adoption intention; and to examine whether innovation adoption readiness strengthens the usefulness-adoption-intention relationship.

The corresponding research questions are: RQ1: How do relative advantage and compatibility shape perceived usefulness of IBM AI/cloud solutions? RQ2: Does perceived usefulness translate into adoption intention? RQ3: Do DOI attributes retain direct effects on adoption intention after usefulness is considered? RQ4: Does perceived usefulness mediate DOI-intention relationships? RQ5: Does innovation adoption readiness alter the strength of the usefulness-intention relationship?

Building on the stated objectives, this subsection clarifies what the study adds to existing knowledge and practice. The contributions are framed at the theoretical, empirical, contextual and methodological levels and are limited to what can be supported by the supplied questionnaire and database.

The study makes four contributions. The theoretical contribution is a mechanism-oriented integration of DOI and TAM. Rather than placing DOI and TAM constructs in parallel, it positions relative advantage and compatibility upstream of perceived usefulness. The empirical contribution is a 385-case analysis of an IBM enterprise-AI context in Bangladesh, using a shared master questionnaire but selecting a model specifically aligned with the research problem. The contextual contribution is to an emerging-market literature in which enterprise AI acceptance is still comparatively under-specified. The practical contribution is diagnostic: the results distinguish between direct value perceptions, usefulness-based mediation and general innovation readiness, allowing organisations to identify whether adoption barriers are primarily about value communication, workflow fit or readiness.

The article also contributes methodologically by reporting the data audit explicitly. The supplied workbook contains 400 respondent IDs but only 385 populated cases. Rather than treating the target of 400 as the empirical sample, the analysis uses the 385 complete observations. This distinction is essential because the article-writing guide explicitly warns that 385 must represent genuine collected or cleaned observations rather than simulated rows [16]. The manuscript therefore reports the actual populated sample and avoids presenting blank rows as respondents.

2. Literature Review and Theoretical Foundation

Building on the problem and gaps established in the introduction, this section develops the theoretical logic required to explain the proposed relationships. The review is organised around the distinction between innovation characteristics, users' cognitive evaluations of usefulness, and the intention to adopt. Diffusion of Innovations (DOI) provides the innovation-level perspective, while the Technology Acceptance Model (TAM) explains how perceived usefulness connects technology evaluations with behavioural intention. The section therefore moves from conceptual clarification to theory, construct-level evidence, hypothesis development, and finally an integrated framework that makes the proposed causal sequence explicit.

2.1. Conceptual Background

The analysis begins by defining enterprise AI from the respondent-facing perspective adopted by the questionnaire. This clarification is important because the study concerns perceived organisational value rather than the technical specification or complete product portfolio of IBM.

Enterprise AI refers here to AI/cloud-enabled digital solutions intended to support organisational or professional activities. The study does not attempt to define IBM's full product portfolio; instead, it adopts the questionnaire's respondent-facing framing of IBM AI/cloud and enterprise technologies. This is appropriate because adoption is assessed from the user's perspective. AI can create value through automation, augmentation, prediction, classification, information processing and decision support, but the realisation of these benefits depends on users' interpretation of what the technology contributes to work [2], [10], [11].

Perceived value is consequently represented through perceived usefulness and the innovation attributes that make usefulness credible. Perceived usefulness captures whether users believe technology improves task performance, operational efficiency and data-driven decision making. Relative advantage captures the perceived superiority of IBM technologies over conventional approaches, while compatibility captures perceived fit with organisational IT needs, workflows and work practices. The constructs are complementary: relative advantage describes why an innovation is better, compatibility describes why it fits, and usefulness describes what the user expects to gain from using it.

Adoption intention is the proximal behavioural outcome in the model. The questionnaire's three items ask whether respondents would consider using suitable IBM AI/cloud solutions, intend to use advanced enterprise technologies in future professional work, and would recommend adoption when organisational needs are met [6]. These items capture willingness to move from evaluation to intended adoption. Because the study is cross-sectional and does not contain objective usage logs, adoption intention should not be interpreted as actual adoption behaviour.

The final construct in this conceptual sequence concerns the respondent's broader orientation toward innovation. Distinguishing readiness from usefulness allows the model to examine whether openness to innovation contributes directly to intention and whether it also conditions the usefulness-intention relationship.

Innovation adoption readiness represents a broader disposition toward organisational technology change. It combines openness to advanced enterprise technologies, willingness to experiment and the perceived importance of innovation for future competitiveness. Conceptually, readiness is distinct from usefulness. A person may believe a technology is useful but remain reluctant to experiment, while a highly innovation-oriented person may express adoption intention even before experiencing the technology directly. This distinction makes readiness a useful direct predictor and a plausible boundary condition.

2.2. Theoretical Foundation

The TAM perspective provides the cognitive foundation for the downstream portion of the model. Particular emphasis is placed on perceived usefulness because the research question concerns how expected work value translates into adoption intention.

The Technology Acceptance Model originated from work on technology acceptance and proposed perceived usefulness and perceived ease of use as central beliefs shaping acceptance [17]-[19]. Perceived usefulness is particularly relevant to workplace technologies because users evaluate systems partly by whether they improve job performance. Subsequent TAM research has shown the durability of usefulness as an explanatory construct across many information-system settings [20], [21]. A systematic review of AI acceptance likewise found perceived usefulness among the most consistently reported predictors of intention, willingness and use behaviour [5].

The present study uses TAM selectively. It does not include perceived ease of use as a central path because the supplied research plan recommends TAM and DOI and the article's substantive focus is perceived value. This is analytically purposeful: the research question is whether innovation characteristics become useful to users and whether that usefulness is translated into adoption intention. The omission of effort expectancy also prevents the model from becoming a generic technology-acceptance omnibus model.

DOI complements TAM by shifting attention from the user's general acceptance belief to perceived characteristics of the innovation itself. The discussion therefore focuses on relative advantage and compatibility as the two DOI dimensions most directly represented in the supplied instrument.

DOI theory explains adoption partly through perceived characteristics of an innovation. Relative advantage reflects the extent to which an innovation is perceived as better than an existing alternative; compatibility concerns consistency with existing values, experience and needs; and complexity, trialability and observability represent additional innovation attributes [14]. Meta-analytic evidence indicates that innovation attributes can influence organisational technology intention and adoption, while the strength of relationships can vary by technology type and country context [22].

For enterprise AI, relative advantage and compatibility are particularly salient. AI technologies often require users to compare new capabilities with established tools and routines. A user who sees a clear operational or competitive benefit has a reason to consider adoption. A user who sees a poor fit with workflows may reject an otherwise useful technology because integration costs and disruption undermine the expected value. The questionnaire captures precisely these two dimensions [6].

Having considered TAM and DOI separately, the next step is to specify how they can be combined without reducing the model to a list of parallel predictors. The proposed integration places DOI attributes upstream of perceived usefulness and retains direct paths so that the empirical analysis can distinguish direct and indirect value-realisation processes.

The integrated model treats DOI attributes as upstream value cues and TAM usefulness as the cognitive mechanism through which those cues become an adoption-relevant judgement. The logic is sequential: perceived relative advantage and compatibility provide information about the innovation; users translate that information into a belief that the technology is useful; usefulness then contributes to adoption intention. Direct DOI-to-intention paths are retained because innovation characteristics can also motivate adoption without being fully translated through usefulness. Innovation adoption readiness is positioned as both a direct predictor and a theoretically plausible moderator of the usefulness-intention link.

2.3. Construct-Specific Literature

The theoretical integration establishes the overall causal logic, while construct-specific evidence provides the more focused justification for each variable. This subsection consequently reviews the empirical and conceptual relevance of the focal constructs before moving to the formal hypotheses.

Relative advantage is one of the most established DOI attributes. Innovations perceived to provide clearer benefits than existing approaches are more likely to receive consideration and support [14], [22]. In enterprise AI, advantage may be interpreted through efficiency, decision support, automation or improved organisational capability. The questionnaire measures this construct through perceived superiority to conventional approaches, improved organisational capabilities and competitive or operational benefits [6].

Compatibility is similarly important because enterprise technologies rarely operate in isolation. Compatibility concerns whether the innovation fits existing needs, workflows and work practices. Organisational adoption research has repeatedly identified fit with routines and infrastructures as relevant to assimilation [23]. For IBM AI/cloud solutions, compatibility is particularly consequential because enterprise systems are embedded in technical and organisational architectures rather than used as standalone consumer applications.

Perceived usefulness is the central TAM construct in the proposed mechanism. It captures expected improvement in task performance, efficiency and data-driven decision making. AI acceptance research indicates that usefulness is frequently associated with behavioural intention [5]. In professional settings, usefulness may be particularly persuasive because users can connect technology value to concrete work outcomes.

Innovation adoption readiness is broader than a specific technology belief. It reflects openness to advanced technologies, willingness to experiment and recognition that innovation matters for competitiveness. Readiness may therefore operate as an enabling condition for adoption. However, its interaction with usefulness is theoretically ambiguous: readiness could strengthen the translation of usefulness into intention, but it could also simply raise intention directly.

Adoption intention is the behavioural-proximal outcome. The study interprets intention as a stated willingness to consider or use suitable IBM AI/cloud solutions rather than actual system use. This distinction follows the evidence that AI acceptance research relies heavily on self-report measures and that future work should validate intentions against naturalistic usage [5].

2.4. Hypotheses Development

Drawing on the preceding conceptual and theoretical discussion, this subsection converts the proposed relationships into formally testable hypotheses. The sequence follows the logic of the model: innovation attributes are first linked to usefulness, usefulness is linked to intention, direct DOI effects are retained, and mediation and moderation are then tested.

Relative Advantage → Perceived Usefulness

The first hypothesis addresses the upstream relationship between an innovation characteristic and the user's value judgement. The theoretical expectation is that comparative superiority should provide a substantive basis for perceiving the technology as useful in professional work.

DOI proposes that relative advantage increases the attractiveness of an innovation because users perceive it as better than an existing alternative [14]. In a TAM interpretation, such comparative benefit provides a basis for judging whether the technology will improve performance. If IBM AI/cloud solutions are seen as offering superior operational or competitive benefits, respondents have stronger reasons to judge them useful for tasks and decision making. Meta-analytic evidence also supports the relevance of innovation attributes to IT adoption [22]. Therefore:

H1: *Relative advantage positively influences perceived usefulness of IBM AI/cloud solutions.*

Compatibility → Perceived Usefulness

The second hypothesis considers whether perceived organisational fit contributes to the formation of usefulness beliefs. This relationship extends the value-realisation logic by recognising that expected benefits are meaningful only when users can connect the innovation to existing needs and work practices.

Compatibility can shape usefulness because a technology that fits existing needs and workflows is easier to connect to actual work outcomes. A technically capable innovation may be judged less useful if it requires disruptive changes to routines or cannot integrate with common enterprise practices. The questionnaire's compatibility items directly capture organisational fit and integration with work practices [6]. DOI research also identifies compatibility as a recurring adoption attribute [14], [22]. Therefore:

H2: *Compatibility positively influences perceived usefulness of IBM AI/cloud solutions.*

Perceived Usefulness → Adoption Intention

The third hypothesis represents the central TAM pathway in the integrated model. After usefulness has been formed through evaluations of the innovation, the model proposes that this belief should translate into greater willingness to consider adoption.

TAM predicts that perceived usefulness contributes directly to behavioural intention [17]-[20]. The AI acceptance literature provides contemporary support for this relationship across multiple application settings [5]. For IT-oriented respondents, a belief that AI improves professional tasks, efficiency and decision making should increase willingness to consider adoption. The relationship is expected even after DOI attributes are controlled because usefulness represents a more proximal cognitive evaluation of expected work value.

H3: *Perceived usefulness positively influences adoption intention.*

Relative Advantage → Adoption Intention

The model does not assume that all DOI effects must pass through usefulness. This subsection therefore tests whether perceived superiority also retains an independent relationship with adoption intention after the usefulness mechanism is taken into account.

Relative advantage can affect intention directly because users may move from comparative evaluation to adoption without requiring a separate usefulness judgement. Seeing a technology as superior to conventional approaches can create an immediate adoption rationale, particularly when competitive or operational benefits are salient. DOI scholarship treats relative advantage as a central driver of innovation adoption [14], [22].

H4: *Relative advantage positively influences adoption intention.*

Compatibility → Adoption Intention

Similarly, perceived compatibility may influence adoption intention through considerations that are not fully captured by task-level usefulness. The hypothesis therefore preserves a direct DOI pathway and permits the empirical model to distinguish complementary mechanisms.

Compatibility can also exert a direct influence because perceived fit reduces uncertainty about organisational disruption and implementation friction. A technology that appears compatible with current workflows may be considered adoptable even before users form a detailed task-performance judgement. Enterprise technology adoption research emphasises the importance of fit between innovations and existing organisational arrangements [23].

H5: *Compatibility positively influences adoption intention.*

Perceived Usefulness as a Mediator

The preceding hypotheses establish both upstream and downstream relationships; the next question is whether usefulness connects them. Mediation is therefore specified as the mechanism through which perceptions of advantage and fit may be translated into an adoption-relevant performance judgement.

The integrated DOI-TAM argument implies that some of the effect of innovation attributes on adoption intention should pass through usefulness. Relative advantage and compatibility provide evaluative information; perceived usefulness translates that information into a work-performance belief; adoption intention is then the behavioural response. This mechanism is more informative than a direct-effects-only model because it distinguishes an innovation characteristic from the cognitive value judgement it generates.

H6: *Perceived usefulness mediates the positive relationship between relative advantage and adoption intention.*

H7: *Perceived usefulness mediates the positive relationship between compatibility and adoption intention.*

Innovation Adoption Readiness as a Boundary Condition

The final hypothesis extends the model from mediation to conditional effects. If readiness represents an enabling orientation toward innovation, it may alter the extent to which usefulness is converted into adoption intention; alternatively, readiness may operate primarily as an independent predictor.

Readiness can be understood as an individual/professional capacity to engage with innovation. Respondents who are open to advanced technologies and willing to experiment may be more able to convert a usefulness judgement into an adoption intention. This implies a positive interaction between usefulness and readiness. However, readiness may instead operate primarily as a direct determinant, in which case the interaction would be weak or absent. Testing the interaction therefore distinguishes these mechanisms.

H8: *Innovation adoption readiness positively moderates the relationship between perceived usefulness and adoption intention, such that the usefulness-intention relationship is stronger at higher levels of readiness.*

2.5. Synthesis of Hypotheses and Model Logic

Taken together, the hypotheses specify a staged value-realisation process rather than a set of unrelated predictors. H1 and H2 locate the first stage at the innovation level: relative advantage and compatibility are expected to shape perceived usefulness. H3 then represents the TAM-consistent translation from usefulness to adoption intention, while H4 and H5 retain direct DOI-to-intention paths to determine whether innovation attributes exert influence beyond usefulness. H6 and H7

formalise the corresponding indirect mechanisms through perceived usefulness. Finally, H8 tests whether innovation adoption readiness changes the strength of the usefulness-intention relationship. This structure permits the analysis to distinguish three analytically different possibilities-direct influence, mediated influence, and conditional influence-within a single parsimonious framework.

2.6. Conceptual Framework

Figure 1 visualises the integrated DOI-TAM model and should be read from left to right as a sequence of value formation and adoption. The two DOI attributes-relative advantage and compatibility-occupy the upstream position because they describe how respondents evaluate the innovation itself. Perceived usefulness is placed centrally because it represents the cognitive judgement through which those innovation characteristics are translated into expected work value. Adoption intention is the distal behavioural-proximal outcome, capturing willingness to consider, use or recommend suitable IBM AI/cloud solutions. Innovation adoption readiness is positioned separately because it reflects the respondent’s broader orientation toward organisational innovation rather than a property of IBM technology itself.

Innovation adoption readiness is shown with a direct path to adoption intention because the construct captures openness to experimentation and the perceived strategic importance of innovation. This direct path is treated as an additional structural relationship rather than as a separately numbered hypothesis in the present model. The dashed interaction path labelled H8 represents the moderation test. It asks whether the strength of the usefulness-intention relationship changes as readiness increases. A significant interaction would indicate a boundary condition; a non-significant interaction, as observed in the present data, instead suggests that readiness may raise the baseline level of intention without materially changing how usefulness translates into intention.

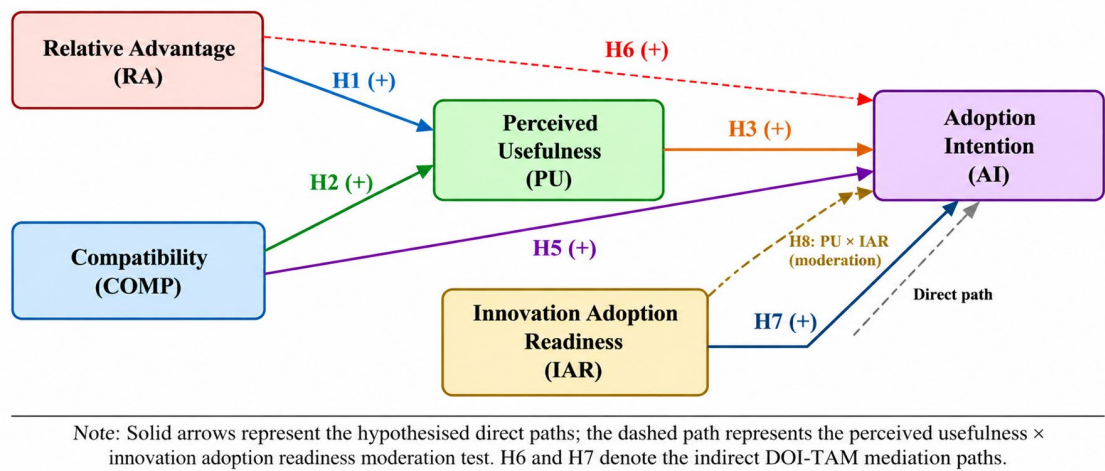


Figure 1. Integrated DOI-TAM value-realization framework. Note. Solid arrows represent the hypothesised direct paths; the dashed path represents the perceived usefulness × innovation adoption readiness moderation test. H6 and H7 denote the indirect DOI-TAM mediation paths.

3. Methodology

The theoretical model requires an empirical design capable of distinguishing antecedent, mediating and moderating relationships while remaining faithful to the supplied questionnaire and database. Accordingly, this section explains the quantitative cross-sectional design, study context, eligibility and sampling approach, measurement instrument, data-collection and ethical procedures, and the analytical strategy used to evaluate the proposed model. Particular attention is given to data screening and measurement assessment because the distinction between substantive findings and measurement limitations is important for interpreting the structural results responsibly.

3.1. Research Design

With the theoretical model established, the methodology must demonstrate how its proposed relationships can be examined empirically. This subsection therefore specifies the overall research design and explains how the analytical approach remains aligned with the supplied research plan and questionnaire.

The study uses a quantitative, cross-sectional, explanatory/predictive survey design, consistent with the supplied research plan. The master questionnaire specifies a structured five-point Likert response format from strongly disagree to strongly agree and recommends reliability, validity, measurement-model assessment and SEM/PLS-SEM for hypothesis testing [6]. The present analysis follows that logic while using transparent composite-score path models that can be reproduced from the supplied workbook. Because the workbook does not include the raw recruitment log, collection dates, platform metadata or a verified institutional ethics identifier, those details are not invented in this manuscript.

3.2. Study Population and Research Context

The intended population comprises IT students, early-career IT professionals, developers and enterprise-technology users in Bangladesh who are familiar with cloud, AI or enterprise systems [9]. The unit of analysis is the individual respondent. Eligibility was operationalised in the questionnaire through age and relevant experience with IBM/enterprise AI or cloud technologies [6]. The supplied dataset contains respondents with varied employment status, education, use frequency and experience length, providing heterogeneity within the intended technology-oriented population.

3.3. Sampling Design and Sample Size

Having defined the target population, this subsection explains how respondents were selected and how the usable sample was determined. The distinction between the planned target and the populated observations is retained to ensure that the reported sample size reflects the database rather than the intended target.

The research plan specifies purposive/criterion-based sampling. This is appropriate for a study that requires respondents to possess relevant technology familiarity rather than representing the general population. The planned target was 400 respondents, with a benchmark of at least 385 valid observations based on Cochran's large-population formula at 95% confidence, 5% margin of error and $p=.50$ [9].

The supplied workbook contains 400 respondent IDs, but only IDs 1-385 contain complete response records. IDs 386-400 are blank across the substantive questionnaire fields. All 385 populated observations have an attention-check value of 4, which is the expected 'Agree' response specified in the codebook. Accordingly, $n=385$ is the final usable sample for the present analysis. No blank row is treated as a respondent.

3.4. Questionnaire Development and Measurement

The questionnaire comprises participant consent, respondent profile, construct measures and optional quality-control items. The supplied Group 5 instrument contains three reflective items for each of the core constructs used in this article: perceived usefulness (PU1-PU3), relative advantage (RA1-RA3), compatibility (COMP1-COMP3), innovation adoption readiness (IAR1-IAR3) and adoption intention (AI1-AI3) [6]. All substantive items use the five-point Likert scale. The exact original item-source bibliography is not supplied in the questionnaire; therefore, this manuscript attributes measurement wording to the supplied master questionnaire and theoretical framing rather than inventing source citations.

To connect the conceptual model with the empirical instrument, Table 1 summarises the five focal constructs, their item codes, operational emphasis, and the source basis specified in the supplied

questionnaire and theoretical framing. This overview establishes the measurement architecture used in the subsequent empirical analysis.

Table 1. Operationalisation of the Focal Constructs.

Construct	Codes	Operational focus	Source basis
Relative Advantage	RA1-RA3	Superiority, capability and competitive/operational benefit	Supplied Group 5 questionnaire; DOI framing
Compatibility	COMP1-COMP3	Fit with IT needs, workflows and work practices	Supplied Group 5 questionnaire; DOI framing
Perceived Usefulness	PU1-PU3	Task performance, efficiency and decision-making value	Supplied Group 5 questionnaire; TAM framing
Innovation Adoption Readiness	IAR1-IAR3	Openness, experimentation and innovation orientation	Supplied Group 5 questionnaire
Adoption Intention	AI1-AI3	Consideration, intended use and recommendation	Supplied Group 5 questionnaire

Note. Construct labels and item codes follow the supplied Group 5 questionnaire and the model terminology used throughout the manuscript.

3.5. Pilot Study and Instrument Refinement

Measurement quality also depends on the instrument-development process. The available materials provide guidance concerning piloting and expert review, but they do not contain a separate pilot dataset or report; this subsection therefore distinguishes documented procedures from information that remains unavailable.

The questionnaire guidance recommends a genuine pilot of approximately 30-50 eligible respondents and expert review by two to three subject/method experts [6]. The supplied files do not provide a separate pilot dataset or a pilot report. Accordingly, no pilot reliability coefficient, item deletion or wording change is claimed here. The absence of documented pilot results limits assessment of instrument development and should be addressed in the study limitations.

3.6. Data Collection Procedure

The research plan specifies an online structured questionnaire. The present database contains 385 complete response records and optional open comments. However, the supplied files do not document the exact recruitment channels, collection dates, response rate or geographic recruitment procedure. The manuscript therefore reports the data source only as the supplied online structured survey dataset and does not fabricate procedural details.

3.7. Ethical Considerations

Ethical procedures are particularly important for survey research involving individual respondents. This subsection therefore records the consent and anonymity information documented in the questionnaire while avoiding claims about formal institutional approval that cannot be verified from the supplied materials.

The questionnaire included an eligibility and voluntary informed-consent section, and the dataset uses respondent IDs rather than names. However, the supplied materials do not establish whether consent was affirmatively recorded for each respondent or whether institutional review or exemption was required. These matters must be verified by the authors before submission. No unverified ethics approval is asserted.

3.8. Data Analysis Strategy

The analysis proceeded in five stages. First, the workbook was audited for blank cases, duplicate IDs, missingness and attention-check performance. Second, descriptive statistics were calculated for respondent characteristics and the five core constructs. Third, internal consistency and convergent/discriminant diagnostics were examined. Fourth, the structural model was estimated using standardised composite scores: relative advantage and compatibility predicted usefulness; usefulness, relative advantage, compatibility and readiness predicted adoption intention; and a centred/standardised usefulness × readiness interaction tested moderation. Fifth, mediation was evaluated using nonparametric bootstrap resampling with 10,000 draws. The model reports coefficients, standard errors, confidence intervals, p-values, R² and effect sizes.

The analysis should be interpreted as a transparent composite-score SEM-aligned implementation rather than as a claim that SmartPLS or another commercial PLS engine was run. This distinction matters because the supplied environment did not provide a native PLS-SEM estimation output. The reported measurement diagnostics therefore function as publication-oriented diagnostics and an implementation-ready specification for a final SmartPLS/ADANCO replication. The article deliberately avoids presenting these results as software-specific PLS estimates.

4. Results

The database audit identified 400 respondent IDs. Rows 386-400 are completely blank across the substantive fields, producing 15 blank cases. The remaining 385 records contain complete responses for the core questionnaire variables. No duplicate respondent IDs were detected. All 385 populated records selected 4 ('Agree') on the attention-check item, exactly matching the expected response in the codebook. The final analytical sample is therefore n=385.

Table 2. Respondent Profile and Technology-Use Characteristics.

Characteristic	Category	n-385	%
Age	18-20	45	11.7
Age	21-25	121	31.4
Age	26-30	109	28.3
Age	31-40	82	21.3
Age	41 or above	28	7.3
Gender	Male	222	57.7
Gender	Female	147	38.2
Gender	Prefer not to say	11	2.9
Gender	Prefer to self-describe	5	1.3
Status	Employed	179	46.5
Status	Student	116	30.1
Status	Self-employed/Freelancer	71	18.4
Status	Other	19	4.9
Education	Undergraduate	126	32.7
Education	Graduate	120	31.2
Education	Postgraduate	126	32.7
Education	Other	13	3.4
Use frequency	Daily	75	19.5
Use frequency	Several times/week	140	36.4
Use frequency	Weekly	104	27.0
Use frequency	Less often	66	17.1
Experience	<6 months	35	9.1
Experience	6-12 months	58	15.1
Experience	1-2 years	116	30.1
Experience	3-5 years	120	31.2

Characteristic	Category	n-385	%
Experience	>5 years	56	14.5
AI-feature experience	Not sure/not aware	28	7.3
AI-feature experience	Aware but not used	113	29.4
AI-feature experience	Occasional user	155	40.3
AI-feature experience	Regular user	89	23.1

Note. Percentages may not sum to exactly 100% within a characteristic because of rounding.

The profile indicates a mixed professional/student sample rather than a purely employed workforce. Employed respondents constitute 46.5%, while students account for 30.1% and self-employed/freelance respondents 18.4%. Technology-use frequency is also heterogeneous: 19.5% report daily use, 36.4% several-times-per-week use, 27.0% weekly use and 17.1% less frequent use. AI-feature experience is similarly varied, with 23.1% regular users and 40.3% occasional users, while 29.4% are aware but report not using the relevant features. This variation supports the decision to examine readiness as a distinct construct rather than assuming a uniform level of technology familiarity.

4.1. Descriptive Statistics

After confirming the analytical sample, descriptive statistics provide the first substantive picture of how respondents evaluated the focal constructs. These estimates are interpreted as distributions of observed perceptions rather than as evidence of causal relationships.

Table 3 reports the descriptive distribution of the five constructs entering the structural model. The means and standard deviations provide an initial indication of the overall level and dispersion of respondents’ evaluations, while the observed minimum and maximum values show the empirical range represented in the usable sample.

Table 3. Descriptive Statistics of the Focal Constructs.

Construct	Mean	SD	Min	Max
RA	3.885	0.522	2.33	5.0
COMP	3.779	0.547	2.0	5.0
PU	4.01	0.521	2.67	5.0
IAR	3.671	0.487	2.0	5.0
AI	3.792	0.482	2.33	5.0

Note. Construct scores are composite means based on the five-point response scale used in the supplied questionnaire.

All five constructs have means above the midpoint of 3.0. Perceived usefulness is highest (M=4.010, SD=0.521), followed by relative advantage (M=3.885, SD=0.522), adoption intention (M=3.792, SD=0.482), compatibility (M=3.779, SD=0.547) and innovation adoption readiness (M=3.671, SD=0.487). The pattern indicates generally favourable evaluations of IBM AI/cloud value, while readiness is comparatively less elevated. This difference is substantively useful: respondents can perceive a technology as useful without being equally strong in their general readiness to experiment with innovation.

4.2. Measurement Model Assessment

Before interpreting structural paths, it is necessary to establish how consistently and distinctly the questionnaire items represent the focal constructs. The measurement assessment therefore considers indicator reliability, internal consistency, convergent validity and discriminant validity in sequence.

One-factor standardised loading diagnostics were calculated for the three-item core constructs. The resulting loading patterns are generally moderate-to-strong, although not every indicator reaches the conventional .70 benchmark. The lowest loading occurs for AI3 (.673 in the one-factor diagnostic),

while the highest is COMP2 (.781). These results suggest that the indicators share a common construct signal but also contain non-trivial item-specific variance.

The measurement assessment is summarised in Table 4 through item loadings, Cronbach’s alpha, composite reliability, and average variance extracted (AVE). Considering these diagnostics jointly allows the reader to distinguish indicator-level performance from construct-level reliability and shared variance.

Table 4. Reliability and Convergent-Validity Diagnostics.

Construct	Item loadings	Cronbach α	Composite reliability*	AVE
PU	0.713, 0.738, 0.705	0.529	0.762	0.517
RA	0.737, 0.679, 0.686	0.483	0.743	0.491
COMP	0.720, 0.781, 0.632	0.515	0.756	0.509
IAR	0.727, 0.649, 0.663	0.419	0.721	0.463
AI	0.690, 0.640, 0.673	0.378	0.707	0.446

Note. *Composite reliability is the loading-based reliability diagnostic reported in the analysis and is interpreted alongside Cronbach’s alpha and AVE.

*Composite reliability is calculated from the standardised one-factor loading diagnostics and is presented as a diagnostic, not as software-generated PLS output. The results reveal a notable measurement-quality constraint. Composite reliability is around or above .70 for the five constructs, but Cronbach’s alpha ranges from .378 to .529. AVE is .517 for usefulness and .509 for compatibility, while relative advantage (.491), readiness (.463) and adoption intention (.446) are slightly below the conventional .50 threshold. These results are not hidden because Q1-level reporting requires transparent treatment of measurement weaknesses. The low alpha values likely reflect the very short three-item scales and modest inter-item correlations, but they still limit confidence in the measurement model.

The convergent-validity evidence is therefore mixed. Perceived usefulness and compatibility reach the conventional AVE benchmark, while relative advantage, innovation adoption readiness and adoption intention fall slightly below it. Because the questionnaire contains only three indicators per construct, deleting an item solely to raise AVE would risk narrowing construct coverage and capitalising on the current sample. No post hoc deletion is therefore recommended for the main manuscript without a theoretically justified and independently validated measurement revision.

Table 5 presents the heterotrait-monotrait (HTMT) ratios used to assess whether the five focal constructs remain empirically distinguishable. The matrix complements the convergent-validity evidence by showing the degree of association between conceptually different constructs.

Table 5. HTMT Discriminant-Validity Matrix.

	RA	COMP	PU	IAR	AI
RA	-	0.618	0.531	0.737	0.644
COMP	0.618	-	0.532	0.618	0.632
PU	0.531	0.532	-	0.539	0.529
IAR	0.737	0.618	0.539	-	0.683
AI	0.644	0.632	0.529	0.683	-

Note. Entries are HTMT ratios; diagonal cells are not applicable.

HTMT values range from .529 to .737, remaining below the commonly used .85 threshold. The highest value is between relative advantage and innovation adoption readiness (.737), followed by readiness and adoption intention (.683). The results therefore provide evidence that the five constructs are empirically distinguishable despite their conceptual relatedness. A separate single-factor diagnostic shows that the first principal component accounts for 20.7% of variance across the

15 core indicators; this is not evidence that common-method bias is absent, but it does not indicate single-factor dominance.

4.3. Structural Model Assessment

Before interpreting the structural coefficients, Table 6 reports variance inflation factor (VIF) values for the predictors entering the endogenous equations. These diagnostics provide a direct check on whether excessive predictor overlap could undermine the stability or interpretability of the estimated relationships.

Table 6. Collinearity Diagnostics for Structural Predictors.

Predictor	VIF
RA	1.221
COMP	1.198
PU	1.165
IAR	1.202
PU×IAR	1.014

Note. VIF values correspond to the structural predictors specified in the proposed model, including the perceived-usefulness × readiness interaction.

All VIF values are low, ranging from approximately 1.01 to 1.22. The structural estimates are therefore not threatened by severe predictor collinearity.

The antecedent model explains 11.6% of the variance in perceived usefulness ($R^2=0.116$). The adoption-intention model explains 15.4% of the variance in adoption intention ($R^2=0.154$). Ten-fold cross-validation produces mean out-of-sample R^2 values of approximately .077 for usefulness and .102 for adoption intention, indicating that the model has modest predictive performance beyond the in-sample explanatory estimates. The relatively low R^2 values are important: the model captures a meaningful but incomplete part of adoption intention, consistent with the broader AI-adoption literature's finding that multiple psychosocial, technological and contextual factors can matter [5], [13].

The hypothesis tests provide the direct empirical evaluation of the relationships specified in Section 2.4. Each path is considered against its predicted direction and statistical evidence, while the non-significant interaction is retained because it is theoretically relevant to the proposed boundary-condition argument.

Table 7 provides the central structural-model evidence by reporting the standardised path coefficients, test statistics, significance levels, confidence intervals, and hypothesis decisions. The table is therefore the principal empirical bridge between the hypotheses developed in Section 2.4 and the results discussed in Sections 4 and 5.

Table 7. Structural Path Estimates and Hypothesis-Test Results.

Hypothesis	Path	β	t	p	95% CI low	95% CI high	Decision
H1	RA → PU	0.204	4.043	<.001	0.105	0.304	Supported
H2	COMP → PU	0.217	4.288	<.001	0.117	0.316	Supported
H3	PU → AI	0.119	2.334	0.020	0.019	0.219	Supported
H4	RA → AI	0.147	2.823	0.005	0.045	0.250	Supported
H5	COMP → AI	0.156	3.024	0.003	0.055	0.258	Supported
H8	PU × IAR → AI	0.039	0.761	0.447	-0.061	0.138	Not supported

Note. β denotes the standardised path coefficient. Confidence intervals are reported as the lower and upper bounds. A reported p value below .001 is shown as <.001.

Relative advantage significantly predicts perceived usefulness ($\beta=.204, t=4.043, p<.001$), supporting H1. Compatibility also predicts perceived usefulness ($\beta=.217, t=4.288, p<.001$), supporting H2. Perceived usefulness predicts adoption intention ($\beta=.119, t=2.334, p=.020$), supporting H3. Both DOI attributes retain significant direct effects on adoption intention: relative advantage ($\beta=.147, t=2.823, p=.005$) and compatibility ($\beta=.156, t=3.024, p=.003$), supporting H4 and H5. Innovation adoption readiness is also a significant direct predictor ($\beta=.150, t=2.895, p=.004$).

The usefulness $\times$ readiness interaction is small and statistically non-significant ($\beta=.039, t=.761, p=.447$; 95% CI $-.061$ to $.138$). H8 is therefore not supported. Importantly, this does not mean readiness is irrelevant: readiness has a positive direct association with adoption intention. The result instead indicates that the strength of the usefulness-to-intention relationship does not materially differ across the observed readiness range.

Statistical significance is complemented by the incremental effect-size estimates in Table 8. These values indicate the additional contribution associated with each predictor in the relevant endogenous equation and help place the magnitude of the observed relationships in context.

Table 8. Incremental Effect Sizes (f^2).

Predictor	f^2
PU	0.014
RA	0.021
COMP	0.024
IAR	0.022
PU $\times$ IAR	0.002

Note. f^2 values represent incremental effect sizes for the predictors included in the structural model.

The largest incremental effect in the adoption-intention equation is compatibility ($f^2=.024$), followed by readiness ($f^2=.022$), relative advantage ($f^2=.021$) and perceived usefulness ($f^2=.014$). The interaction has a negligible incremental effect ($f^2=.002$). These are small effect sizes, reinforcing the interpretation that adoption intention is multi-determined and that no single predictor dominates the model.

4.5. Mediation Analysis

Because the DOI-TAM model proposes perceived usefulness as a value-realisation mechanism, Table 9 reports the bootstrap indirect effects corresponding to H6 and H7. The confidence intervals provide the basis for evaluating whether the indirect paths from the DOI attributes to adoption intention through usefulness are statistically supported.

Table 9. Bootstrap Indirect Effects for the Mediation Hypotheses.

Hypothesis	Indirect path	Bootstrap indirect effect	95% CI	Decision
H6	RA $\rightarrow$ PU $\rightarrow$ AI	0.025	0.003 to 0.052	Supported
H7	COMP $\rightarrow$ PU $\rightarrow$ AI	0.026	0.004 to 0.053	Supported

Note. Bootstrap indirect effects are reported with their corresponding confidence-interval bounds; an interval that excludes zero supports the indirect effect under the analysis used.

The bootstrap analysis supports both mediation hypotheses. The indirect effect of relative advantage through perceived usefulness is approximately 0.025 (95% CI [0.003, 0.052]), while the indirect effect of compatibility through usefulness is approximately 0.026 (95% CI [0.004, 0.053]). Because both direct effects remain significant after usefulness is included, the pattern is consistent with partial rather than full mediation. The estimated total effects are approximately .172 for relative advantage and .182 for compatibility, implying that roughly 14% of each total effect is transmitted through usefulness. The mediation is therefore statistically detectable but substantively modest.

The preceding analyses provide several complementary pieces of evidence. This subsection integrates the supported direct paths, indirect effects and non-significant interaction into a concise empirical account that serves as the bridge to the theoretical discussion.

The results support the central DOI-TAM value-realisation mechanism. Relative advantage and compatibility both increase perceived usefulness, and usefulness in turn increases adoption intention. The two DOI attributes also retain direct effects on intention, indicating that value perceptions are not exhausted by the usefulness construct. Innovation adoption readiness independently predicts intention but does not significantly moderate the usefulness-intention relationship. The model therefore supports a partial mediation interpretation with readiness functioning more strongly as a direct enabling factor than as a contingency.

5. Discussion

The central empirical finding is that respondents do not appear to evaluate IBM AI/cloud adoption through a single cognitive route. Relative advantage and compatibility both contribute to perceived usefulness, and usefulness contributes to adoption intention, but the DOI attributes also retain direct effects. This pattern is consistent with a value-realisation process in which innovation characteristics matter both because they shape a usefulness judgement and because they independently signal that adoption is worthwhile. The model therefore adds nuance to a standard TAM interpretation without replacing TAM's usefulness mechanism.

The second important finding is that innovation adoption readiness has a direct positive association with adoption intention but does not moderate the usefulness-intention link. Readiness therefore appears to operate as an adoption resource rather than a condition that changes the marginal effect of usefulness. This distinction is theoretically informative because it prevents the common assumption that every readiness variable must be a moderator.

5.1. Finding 1: DOI Attributes Shape Usefulness

Both relative advantage and compatibility significantly predict perceived usefulness, with compatibility having the slightly larger standardised coefficient in the usefulness equation ($\beta=.217$ versus $\beta=.204$). This supports the proposition that users form usefulness judgements partly from how they evaluate the innovation itself. DOI theory predicts that perceived superiority and fit influence adoption because they make the innovation meaningful relative to the status quo [14]. The present evidence extends that logic by showing that these attributes are not merely adoption triggers; they are associated with the intermediate belief that the technology will improve work. [14], [22], [23].

The result is especially relevant for enterprise AI. AI systems are often promoted through technical capabilities, but users experience them through workflows. Relative advantage answers the question 'What is better than what I already use?', whereas compatibility answers 'Can this become part of how I already work?'. The slightly stronger compatibility coefficient suggests that, in this sample, workflow fit may be at least as important as comparative superiority in shaping usefulness. This should not be interpreted as a universal ranking; rather, it is a sample-specific coefficient pattern that suggests enterprise-AI communication should make integration consequences visible. [2], [10], [11], [23].

The finding also aligns with meta-analytic evidence that DOI attributes influence IT innovation adoption while their effects can depend on technology and country context [22]. In Bangladesh, where enterprise digital transformation can involve heterogeneous organisational capabilities and infrastructures, compatibility may be particularly salient because perceived value depends on whether a new solution can connect to existing practices. The result therefore provides contextual support for treating DOI attributes as upstream cognitive inputs to TAM rather than as isolated predictors.

5.2. Finding 2: Usefulness Provides a Partial Value-Realisation Mechanism

Perceived usefulness has a positive association with adoption intention ($\beta=.119$, $p=.020$), and both indirect effects through usefulness are statistically positive. This supports TAM's central proposition while providing a more specific interpretation for enterprise AI: perceived usefulness is a transmission mechanism through which innovation attributes become adoption-relevant. The evidence is consistent with the large AI-acceptance literature showing usefulness as a recurrent predictor of intention [5].

However, the direct effects of relative advantage and compatibility remain significant after usefulness is included. The mechanism is therefore partial rather than complete. This is theoretically important. If usefulness fully absorbed DOI effects, the implication would be that users care about innovation attributes only insofar as those attributes change performance beliefs. Instead, the residual direct effects suggest that comparative superiority and organisational fit have additional motivational content. A user may intend to adopt because a solution appears strategically superior or institutionally compatible even when the specific task-performance judgement captured by PU is not the whole story. [14], [17], [20], [22].

The magnitude of the indirect effects is modest. This is not a weakness to be concealed; it is a substantive result. The data indicate that usefulness is a statistically meaningful but incomplete pathway. Other constructs available in the master questionnaire-such as trust, performance expectancy, effort expectancy, technology readiness and digital skills readiness-may explain additional variance. The research plan deliberately allows each student article to select constructs relevant to its own theoretical model [6]. The present study therefore treats the modest R^2 as evidence that enterprise AI adoption is multi-dimensional rather than as a reason to overfit the model.

5.3. Finding 3: Readiness Matters Directly, Not Interactively

Innovation adoption readiness is positively associated with adoption intention ($\beta=.150$, $p=.004$). This finding indicates that respondents who perceive their professional environment as open to advanced technologies, are willing to experiment and see innovation as important for future competitiveness tend to report stronger adoption intentions. The result is consistent with the conceptual distinction between technology value and change orientation: even a useful technology requires a user who is prepared to engage with innovation. [5], [13].

The interaction between usefulness and readiness is not significant. This result means that the positive association between usefulness and adoption intention does not materially change across readiness levels in the observed sample. Theoretically, this suggests that readiness may not be a 'conversion amplifier'. Instead, it may shift the baseline level of adoption intention. A respondent who is ready for innovation may be more willing to adopt, but the incremental value of perceiving IBM technology as useful appears broadly similar across readiness levels. [5], [13].

This non-significant moderation is valuable because it prevents an overly simple readiness narrative. In organisational interventions, it may be tempting to assume that increasing readiness will automatically make usefulness perceptions more influential. The data do not support that claim. A more defensible interpretation is that readiness and usefulness contribute through partly independent channels. Training and experimentation opportunities may increase readiness, while demonstrations and workflow evidence may increase usefulness; neither should be treated as a substitute for the other.

5.4. Additional and Unexpected Findings

Beyond the focal hypotheses, the empirical assessment reveals measurement and explanatory-power considerations that affect the confidence with which the model should be interpreted. These findings are important because they qualify the substantive results without negating them.

The most notable measurement-related finding is the divergence between Cronbach's alpha and composite reliability. Alpha values are low across the five constructs, while loading-based composite

reliability is around or above .70. This pattern is partly consistent with the known sensitivity of alpha to short scales, but the magnitude of the alpha values means that measurement uncertainty must remain visible. The article therefore does not claim that the measurement model is unequivocally strong. Instead, the structural results are interpreted as evidence from a three-item survey instrument that warrants replication with more extensively validated scales.

A second notable result is the relatively low explanatory power of the adoption-intention model. $R^2=.154$ means that the tested constructs explain approximately 15.4% of variance. This may reflect the deliberately focused model, but it also suggests that adoption intention in enterprise AI depends on additional determinants. The master questionnaire contains several candidates, including trust, performance expectancy, effort expectancy and digital skills readiness. Their exclusion here is theoretically motivated rather than evidence that they are unimportant.

5.5. Integrated Interpretation

The separate findings can now be recombined into a coherent explanation of enterprise-AI value realisation. This synthesis links innovation characteristics, usefulness, intention and readiness while maintaining the methodological caution required by the cross-sectional and self-reported design.

Taken together, the findings support a staged interpretation of enterprise-AI value perception. First, respondents assess whether the innovation offers an advantage and fits existing organisational practices. Second, these assessments contribute to a judgement that the technology is useful. Third, usefulness contributes to adoption intention, while relative advantage and compatibility retain additional direct influence. Fourth, innovation readiness raises intention directly but does not change the usefulness-to-intention slope. The resulting model is therefore neither a pure DOI model nor a pure TAM model. It is an integrated value-realisation account in which innovation characteristics, usefulness beliefs and readiness operate at different levels of the adoption process.

This interpretation is compatible with broader AI research emphasising that technology value emerges through human-AI interaction and organisational context [10], [11]. It also responds to recent calls for AI-adoption research to examine interrelations among determinants rather than treating them as independent variables [13]. The Bangladesh evidence consequently supports a more process-oriented view of enterprise AI adoption, while remaining appropriately cautious about causality because the data are cross-sectional and self-reported.

6. Theoretical and Practical Implications

6.1. Theoretical Implications

The empirical pattern has implications for how DOI and TAM can be combined in enterprise-AI research. This subsection therefore moves from individual findings to theoretical meaning, distinguishing confirmation of established propositions from extensions generated by the integrated model.

The first theoretical implication concerns what the findings confirm about established acceptance theory. The discussion then identifies how the present model extends that logic by positioning usefulness within an explicit DOI-based antecedent structure.

The first theoretical contribution is confirmation of the usefulness mechanism central to TAM in an enterprise-AI context. Perceived usefulness is positively related to adoption intention, consistent with the long-standing TAM proposition [17]-[20] and recent AI-acceptance evidence [5]. At the same time, the study extends TAM by locating usefulness within a DOI pathway. Rather than treating usefulness as an isolated belief, the model shows that perceived innovation characteristics help explain why usefulness forms. [5], [17], [19], [20].

The second implication concerns the mechanism added by the study. By observing both direct and indirect effects, the analysis provides a basis for interpreting usefulness as a bridge between innovation attributes and adoption intention rather than as an isolated TAM predictor.

The second contribution is the explicit mediation of DOI attributes through usefulness. Both relative advantage and compatibility show positive indirect effects through perceived usefulness, while their direct effects remain significant. This partial mediation suggests that innovation attributes influence adoption through both cognitive usefulness and additional direct evaluative routes. The result provides a mechanism-level bridge between two influential theories and may help future research distinguish innovation characteristics from the user beliefs they generate. [14], [20], [22].

The theoretical contribution must also be considered in relation to the empirical setting. Evidence from technology-oriented respondents in Bangladesh provides a context in which the portability of the integrated logic can be considered without assuming that the observed relationships are universal.

The third contribution is contextual. Much of the AI-adoption literature is distributed across consumer AI, healthcare, education, public services and specific industrial applications [5], [13]. This study contributes evidence from technology-oriented respondents in Bangladesh considering enterprise AI/cloud solutions. The context matters because organisational compatibility and professional readiness may be interpreted differently where digital capabilities and organisational infrastructures are heterogeneous. The findings therefore support the portability of TAM-DOI logic while also showing that its explanatory power remains incomplete. [7], [8], [13].

6.2. Practical and Managerial Implications

First, enterprise-AI providers and implementation teams should communicate value in comparative and task-specific terms. Relative advantage predicts both usefulness and adoption intention. Demonstrations should therefore show what improves relative to an existing workflow rather than merely listing AI capabilities. For example, an implementation narrative can connect AI-enabled analytics or automation to a concrete task, baseline process and expected operational improvement.

Second, compatibility deserves explicit implementation attention. Its coefficient is slightly larger than relative advantage in predicting usefulness and it also has a significant direct association with intention. Organisations should therefore treat integration, workflow fit and interoperability as value issues rather than solely technical issues. User-facing pilots should show how the solution fits existing systems and professional routines.

Third, managers should distinguish usefulness-building interventions from readiness-building interventions. Readiness has a direct association with adoption intention, so professional environments that support experimentation and technology learning may create a more receptive adoption climate. However, the non-significant interaction indicates that readiness should not be expected to amplify the usefulness effect automatically. Training and experimentation should therefore complement, rather than replace, demonstrations of practical usefulness.

Fourth, the modest R^2 cautions against one-factor adoption strategies. Providers should not assume that communicating usefulness alone will explain enterprise AI adoption. Trust, skills, effort, organisational support, risk and other factors may contribute. The master questionnaire itself contains these additional constructs, offering a basis for future group-specific models. In practice, adoption programmes should combine value demonstration, integration support, skills development and responsible-use safeguards.

6.3. Policy and Societal Implications

At a broader level, the findings can inform discussion of enterprise-AI capability development within Bangladesh's digital transformation environment. The implications remain bounded by the variables actually measured, particularly because the study does not directly assess privacy, security, fairness or realised productivity.

For Bangladesh's digital transformation ecosystem, the results suggest that AI adoption is not only a matter of access to technology. Perceived fit, professional readiness and credible demonstrations of value can influence whether enterprise AI is considered adoptable. Training

initiatives should therefore combine technical skills with workflow-level understanding and responsible AI practices. Because the study does not measure privacy, security, fairness or actual productivity outcomes in the focal model, policy conclusions should remain limited to the adoption mechanism tested here.

7. Conclusion, Limitations and Future Research

The final substantive section brings the argument back to the research problem and evaluates the contribution of the study as a whole. It first consolidates the central empirical message, then specifies what the integrated model adds to the literature, before identifying limitations that qualify interpretation. These limitations are not treated merely as formal caveats; each is connected to a concrete direction for future research, including stronger measurement, broader samples, longitudinal designs and the use of behavioural evidence alongside stated adoption intention.

This study examined the perceived value and adoption intention of IBM AI/cloud solutions among technology-oriented respondents in Bangladesh using an integrated DOI-TAM framework. The analysis moved beyond a simple list of adoption predictors by specifying a value-realisation pathway: relative advantage and compatibility were positioned as innovation-level antecedents, perceived usefulness as the central cognitive mechanism, and adoption intention as the behavioural-proximal outcome. Innovation adoption readiness was also tested as both a direct predictor and a boundary condition.

The empirical results support the central pathway. Relative advantage and compatibility significantly predict perceived usefulness; perceived usefulness significantly predicts adoption intention; and both DOI attributes retain direct effects on adoption intention. Bootstrap results indicate positive indirect effects through usefulness, consistent with partial mediation. Innovation adoption readiness independently predicts adoption intention, but the usefulness $\times$ readiness interaction is not significant. The findings therefore suggest that enterprise-AI adoption is shaped by both technology-value perceptions and readiness for innovation, but that readiness does not materially change how usefulness translates into intention.

The study's contribution is consequently not that TAM or DOI is sufficient on its own. Instead, the evidence indicates that the two perspectives can be connected through a mechanism that distinguishes innovation attributes from the usefulness judgement they generate. This offers a more nuanced explanation of enterprise AI adoption in an emerging-market context.

The main contribution is a parsimonious, mechanism-oriented model that treats perceived usefulness as a value-realisation bridge between DOI innovation attributes and adoption intention. This approach is distinctive from parallel-predictor models because it asks how users convert perceptions of superiority and fit into a work-performance judgement. The model also demonstrates the value of reporting non-significant moderation rather than selectively presenting only significant relationships. In this sample, readiness is better interpreted as a direct adoption resource than as a condition that strengthens the usefulness effect.

Several limitations constrain interpretation. First, the design is cross-sectional, so the estimated relationships should not be treated as causal. Second, all focal variables are self-reported and measured in the same questionnaire, creating potential common-method concerns despite the absence of single-factor dominance. Third, purposive/criterion-based sampling limits statistical generalisability beyond the target population. Fourth, the sample includes students as well as employed and self-employed respondents, so it should not be described as a pure employee sample. Fifth, the measurement diagnostics reveal low Cronbach alpha values and marginal AVE for several constructs. Sixth, the supplied files do not document exact recruitment dates/channels, pilot results, ethics-approval identifiers or original item-source references. Finally, adoption intention is not actual system use.

Future research should first replicate the model with fully validated multi-item measures whose original sources and psychometric histories are documented. A larger, probability-based sample of employed IT professionals would improve generalisability. Longitudinal research could test whether

perceived usefulness and compatibility measured before implementation predict subsequent use behaviour and realised performance. Multi-group analysis could examine whether the structural paths differ by AI experience, employment status, technology-use frequency or organisational role, provided that group sizes and measurement invariance are adequate.

Future models could also integrate the other constructs available in the master questionnaire. Trust, effort expectancy, performance expectancy and digital skills readiness may explain variance left unexplained by the present focused model. Objective behavioural data, such as actual feature usage or implementation milestones, would provide stronger evidence than intention alone. Finally, qualitative interviews could explore why compatibility remains a significant direct predictor after usefulness is controlled and why readiness operates directly but not interactively. Such mixed-method evidence could reveal organisational mechanisms that survey items cannot capture.

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Ethics Approval: This study used a voluntary questionnaire with an informed-consent section and age-eligibility screening. The analytical dataset contains respondent identifiers rather than participant names. No formal institutional ethics-approval letter or exemption determination was provided for verification; therefore, the authors do not claim institutional review-board approval. Before submission, the authors must confirm the actual consent administration, confidentiality safeguards and applicable institutional and journal ethics requirements. Where required, an institutional determination must be obtained; absence of a local review board does not itself establish exemption.

Informed Consent: The questionnaire provided a voluntary-participation and consent section. The authors must verify that affirmative consent was obtained from every included participant before using this declaration in a journal submission. Participation and withdrawal procedures should be described in accordance with the actual field protocol.

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Appendix A. Core Analytical Codebook

For reproducibility, Table 10 consolidates the item ranges, construct names, structural roles, and item counts used in the focal model. This codebook links the questionnaire-level variables to the analytical specification and provides a concise reference for replication of the reported composite-score analysis.

Table 10. Core Analytical Codebook.

Variable	Construct	Role in model	Items
RA1-RA3	Relative Advantage	Exogenous DOI construct	3
COMP1-COMP3	Compatibility	Exogenous DOI construct	3
PU1-PU3	Perceived Usefulness	Mediator/endogenous construct	3
IAR1-IAR3	Innovation Adoption Readiness	Direct predictor + moderator	3
AI1-AI3	Adoption Intention	Dependent construct	3

Note. Each focal construct is represented by three questionnaire items in the supplied instrument.

Excluded master-dataset constructs: PE1-PE3 (Performance Expectancy), EE1-EE3 (Effort Expectancy), TR1-TR3 (Trust), TRI1-TRI3 (Technology Readiness), DSR1-DSR3 (Digital Skills Readiness), and IAI1-IAI3. They remain part of the supplied database but are outside the focal DOI-TAM model. This preserves model distinctiveness across the shared group dataset.

References

1. Y. K. Dwivedi et al., "Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy," International Journal of Information Management, vol. 57, Art. 101994, 2021, doi: 10.1016/j.ijinfomgt.2019.08.002.
2. M. H. Jarrahi, "Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making," Business Horizons, vol. 61, no. 4, pp. 577-586, 2018, doi: 10.1016/j.bushor.2018.03.007.
3. S. Raisch and S. Krakowski, "Artificial intelligence and management: The automation-augmentation paradox," Academy of Management Review, vol. 46, no. 1, pp. 192-210, 2021, doi: 10.5465/amr.2018.0072.
4. M.-H. Huang and R. T. Rust, "A strategic framework for artificial intelligence in marketing," Journal of the Academy of Marketing Science, vol. 49, pp. 30-50, 2021, doi: 10.1007/s11747-020-00749-9.
5. S. Kelly, S.-A. Kaye, and O. Oviedo-Trespalacios, "What factors contribute to the acceptance of artificial intelligence? A systematic review," Telematics and Informatics, vol. 77, Art. 101925, 2023, doi: 10.1016/j.tele.2022.101925.
6. Group 5 Master Questionnaire, "Questionnaire 5: Group 5 - IBM," CSE and CSIT, Summer 2026, supplied project document.
7. M. M. H. Emon, F. Hassan, M. H. Nahid, and V. Rattanawiboonsom, "Predicting adoption intention of artificial intelligence: A study on ChatGPT," AIUB Journal of Science and Engineering, vol. 22, no. 2, 2023, doi: 10.53799/ajse.v22i2.797.
8. "Application of the technology acceptance model to assess the use and preferences of ICTs among field-level extension officers in Bangladesh," Digital Geography and Society, vol. 3, Art. 100027, 2022, doi: 10.1016/j.diggeo.2022.100027.
9. Research Plan, "IBM Perceived Value of IBM Artificial Intelligence Solutions among IT Professionals in Bangladesh," supplied project document, 2026.
10. M. H. Jarrahi, "Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making," Business Horizons, vol. 61, no. 4, pp. 577-586, 2018.
11. S. Raisch and S. Krakowski, "Artificial intelligence and management: The automation-augmentation paradox," Academy of Management Review, vol. 46, no. 1, pp. 192-210, 2021.
12. A. A. Khanfar, R. K. Mavi, M. Iranmanesh, and D. Gengatharen, "Determinants of artificial intelligence adoption: Research themes and future directions," Information Technology and Management, vol. 27, pp. 31-51, 2026, doi: 10.1007/s10799-024-00435-0.
13. S. Chauhan, P. Gupta, and S. Goyal, "The role of innovation type and country context in diffusion of innovative technologies in organisations: A meta-analytic review," Behaviour & Information Technology, vol. 42, no. 11, 2023, doi: 10.1080/0144929X.2022.2100826.
14. E. M. Rogers, Diffusion of Innovations, 5th ed. New York, NY, USA: Free Press, 2003.
15. F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," MIS Quarterly, vol. 13, no. 3, pp. 319-340, 1989, doi: 10.2307/249008.
16. Article Writing Structure, "Targeted Quantitative Research Article," supplied project document, 2026.

17. F. D. Davis, "A technology acceptance model for empirically testing new end-user information systems: Theory and results," Ph.D. dissertation, MIT, Cambridge, MA, USA, 1985.
18. F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User acceptance of computer technology: A comparison of two theoretical models," *Management Science*, vol. 35, no. 8, pp. 982-1003, 1989, doi: 10.1287/mnsc.35.8.982.
19. F. D. Davis, "User acceptance of information technology: System characteristics, user perceptions and behavioral impacts," *International Journal of Man-Machine Studies*, vol. 38, no. 3, pp. 475-487, 1993.
20. V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: Four longitudinal field studies," *Management Science*, vol. 46, no. 2, pp. 186-204, 2000, doi: 10.1287/mnsc.46.2.186.11926.
21. V. Venkatesh, J. Y. L. Thong, and X. Xu, "Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology," *MIS Quarterly*, vol. 36, no. 1, pp. 157-178, 2012.
22. V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Quarterly*, vol. 27, no. 3, pp. 425-478, 2003.
23. G. C. Moore and I. Benbasat, "Development of an instrument to measure the perceptions of adopting an information technology innovation," *Information Systems Research*, vol. 2, no. 3, pp. 192-222, 1991.
24. L. G. Tornatzky and K. J. Klein, "Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings," *IEEE Transactions on Engineering Management*, vol. 29, no. 1, pp. 28-45, 1982.
25. J. Hair, J. Risher, M. Sarstedt, and C. Ringle, "When to use and how to report the results of PLS-SEM," *European Business Review*, vol. 31, no. 1, pp. 2-24, 2019.
26. J. F. Hair and A. Alamer, "Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example," *Research Methods in Applied Linguistics*, vol. 1, no. 3, Art. 100027, 2022, doi: 10.1016/j.rmal.2022.100027.
27. J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed. Thousand Oaks, CA, USA: Sage, 2022.
28. H. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *Journal of the Academy of Marketing Science*, vol. 43, pp. 115-135, 2015, doi: 10.1007/s11747-014-0403-8.
29. M. R. Ab Hamid, W. Sami, and M. M. Sidek, "Discriminant validity assessment: Use of Fornell & Larcker criterion versus HTMT criterion," *Journal of Physics: Conference Series*, vol. 890, 2017.
30. M. Sarstedt, C. M. Ringle, J. F. Hair, "Partial least squares structural equation modeling," in *Handbook of Market Research*, C. Homburg, M. Klarmann, and A. Vomberg, Eds. Cham, Switzerland: Springer, 2017.
31. S. Xu, K. F. Kee, W. Li, M. Yamamoto, and R. E. Riggs, "Examining the diffusion of innovations from a dynamic, differential-effects perspective: A longitudinal study on AI adoption among employees," *Communication Research*, vol. 51, no. 7, pp. 843-866, 2024, doi: 10.1177/00936502231191832.
32. "Adoption of artificial intelligence in higher education: A diffusion of innovation approach," *The TQM Journal*, vol. 38, no. 3, pp. 633-654, 2026, doi: 10.1108/TQM-12-2024-0523.
33. S. Assidi, M. Omran, T. Rana, and H. Borgi, "The role of AI adoption in transforming the accounting profession: A diffusion of innovations theory approach," *Journal of Accounting & Organizational Change*, vol. 21, no. 5, pp. 915-936, 2025, doi: 10.1108/JAOC-04-2024-0124.
34. "Exploring determinants influencing artificial intelligence adoption, reference to diffusion of innovation theory," *Technology in Society*, vol. 79, Art. 102750, 2024, doi: 10.1016/j.techsoc.2024.102750.
35. "Determinants of public sector managers' intentions to adopt AI in the workplace," *International Journal of Public Administration in the Digital Age*, vol. 11, no. 1, 2024.
36. "The mediating role of attitude towards the technology in shaping artificial intelligence usage among professionals," *Telematics and Informatics Reports*, vol. 17, Art. 100188, 2025, doi: 10.1016/j.teler.2025.100188.
37. M. Glikson and A. W. Woolley, "Human trust in artificial intelligence: Review of empirical research," *Academy of Management Annals*, vol. 14, no. 2, pp. 627-660, 2020, doi: 10.5465/annals.2018.0057.
38. C. C. Castelo, M. W. Bos, and D. R. Lehmann, "Task-dependent algorithm aversion," *Journal of Marketing Research*, vol. 56, no. 5, pp. 809-825, 2019.

39. B. Dietvorst, J. P. Simmons, and C. Massey, "Algorithm aversion: People erroneously avoid algorithms after seeing them err," *Journal of Experimental Psychology: General*, vol. 144, no. 1, pp. 114-126, 2015.
40. J. J. Logg, J. A. Minson, and D. A. Moore, "Algorithm appreciation: People prefer algorithmic to human judgment," *Organizational Behavior and Human Decision Processes*, vol. 151, pp. 90-103, 2019.
41. S. Mikalef and M. Gupta, "Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance," *Information & Management*, vol. 58, no. 3, Art. 103434, 2021.
42. W. W. Wamba-Taguimdje, S. Fosso Wamba, J. R. Kala Kamdjoug, and C. E. Tchatchouang Wanko, "Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects," *Business Process Management Journal*, vol. 26, no. 7, pp. 1893-1924, 2020.
43. T. Davenport, A. Guha, D. Grewal, and T. Bressgott, "How artificial intelligence will change the future of marketing," *Journal of the Academy of Marketing Science*, vol. 48, pp. 24-42, 2020.
44. A. R. He, K. K. Zhang, and others, "Artificial intelligence and digital transformation: Organisational adoption and implementation perspectives," *International Journal of Information Management*, 2022.
45. K. Dwivedi et al., "Setting the future of digital and social media marketing research: Perspectives and research propositions," *International Journal of Information Management*, vol. 59, Art. 102168, 2021.
46. R. H. Chen, "Exploring the impact of technology readiness on technology adoption," *Journal of Business Research*, 2021.
47. M. K. Al-Emran, V. Mezhyuev, and A. Kamaludin, "Technology acceptance model in education and technology adoption: A systematic review," *Education and Information Technologies*, 2018.
48. A. Marikyan and S. Papagiannidis, "Unified theory of acceptance and use of technology: A review," in *TheoryHub Book*, 2023.
49. P. Bagozzi, "The legacy of the technology acceptance model and a proposal for a paradigm shift," *Journal of the Association for Information Systems*, vol. 8, no. 4, pp. 244-254, 2007.
50. S. Benbasat and H. Barki, "Quo vadis, TAM?" *Journal of the Association for Information Systems*, vol. 8, no. 4, pp. 211-218, 2007.
51. Y. Y. Kim, H. J. Chun, and J. Y. Lee, "Determinants of information technology adoption: A meta-analysis of technology acceptance research," *Information Systems Research*, 2019.
52. A. Burton-Jones and G. S. Hubona, "The mediation of external variables in the technology acceptance model," *Information & Management*, vol. 43, no. 6, pp. 706-717, 2006.
53. S. K. Sharma, A. G. Yetton, and J. J. Crawford, "Establishing the structural model for technology adoption," *Information Systems Journal*, 2006.
54. D. Gefen, E. Karahanna, and D. W. Straub, "Trust and TAM in online shopping: An integrated model," *MIS Quarterly*, vol. 27, no. 1, pp. 51-90, 2003.
55. P. A. Pavlou, "Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model," *International Journal of Electronic Commerce*, vol. 7, no. 3, pp. 101-134, 2003.

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