

Technology Readiness as a Higher-Order Driver of Perceived Ease and Usefulness of AI Tools

Imanuella Yesha Metanoia¹, Ghea Sekar Palupi²

^{1,2}*Universitas Negeri Surabaya, Surabaya, Indonesia*

imanuellayesha.22028@mhs.unesa.ac.id , gheapalupi@unesa.ac.id

ABSTRACT

Whether creative professionals embrace artificial intelligence (AI) depends not only on the tools themselves but on the psychological disposition users bring to technology. This study investigates technology readiness as a higher-order driver of the perceived ease of use and perceived usefulness that underpin AI adoption among Indonesian digital creatives. Grounded in the Technology Readiness and Acceptance Model (TRAM), technology readiness is modeled as a second-order reflective construct comprising two enabler dimensions, optimism and innovativeness, and two inhibitor dimensions, discomfort and insecurity, and is linked to perceived ease of use and perceived usefulness. Data from 355 practitioners were analyzed using partial least squares structural equation modeling (PLS-SEM) with the repeated-indicators approach and 5,000 bootstrap resamples. The higher-order construct was valid and reliable, and all four dimensions loaded significantly, with the reverse-coded inhibitor dimensions, insecurity and discomfort, carrying the highest loadings, followed by optimism and innovativeness. Technology readiness significantly and positively influenced both perceived ease of use and perceived usefulness, and perceived ease of use strongly influenced perceived usefulness. Perceived ease of use also partially mediated the effect of technology readiness on perceived usefulness. The findings show that overcoming discomfort and insecurity is as central to readiness as optimism and innovativeness, and that a favorable disposition makes AI tools feel both easier to use and, through that, more useful. The study contributes a dimension-level understanding of technology readiness and offers guidance for cultivating AI readiness in the creative industry.

Keywords: technology readiness, higher-order construct, optimism, insecurity, perceived ease of use, artificial intelligence adoption.

Article Info:

Article history:

Received April 14, 2026

Revised May 18, 2026

Accepted June 22, 2026

Corresponding Author

Imanuella Yesha Metanoia

Universitas Negeri Surabaya, Surabaya, Indonesia

imanuellayesha.22028@mhs.unesa.ac.id

1. INTRODUCTION

Artificial intelligence (AI) is reshaping creative and marketing work, offering tools that assist with design, content generation, and ideation [1], [2]. Adoption in Indonesia is high, with the Microsoft Work Trend Index reporting that 92 percent of Indonesian workers already use generative AI at work [1]. Whether practitioners actually benefit from these tools, however, depends first on their willingness to engage with technology at all. Faced with the same AI tool, one person may explore it with confidence while another hesitates out of unease. This

variation reflects technology readiness, a stable psychological disposition toward technology that precedes any evaluation of a specific system.

Technology readiness, as defined in the Technology Readiness Index (TRI), is a multidimensional construct combining two enablers, optimism and innovativeness, and two inhibitors, discomfort and insecurity [3], [4]. Within the Technology Readiness and Acceptance Model (TRAM), this disposition is theorized to shape perceived ease of use and perceived usefulness, the two central constructs of the Technology Acceptance Model [5], [6]. Yet many studies treat readiness either as a single undifferentiated variable or as four disconnected predictors, obscuring how the dimensions jointly constitute readiness and how strongly this disposition drives the perceived ease of use and perceived usefulness that matter for AI adoption [7]-[10].

This gap is especially consequential in the AI-driven creative industry, where inhibiting reactions such as fear of obsolescence and discomfort with automation are highly salient, yet these inhibitor dimensions are routinely omitted from readiness measurement. Clarifying the internal structure of readiness, identifying which dimensions define it most, and quantifying how strongly it shapes perceived ease of use and perceived usefulness would help educators and organizations design targeted interventions to build AI readiness.

Accordingly, this study addresses the research question: does technology readiness, modeled as a higher-order construct, significantly affect perceived ease of use and perceived usefulness of AI-based creative marketing tools among Indonesian digital creatives, how do its dimensions contribute, and does perceived ease of use channel the effect of readiness on perceived usefulness? The study models technology readiness as a second-order reflective construct, consistent with its conceptualization in TRAM [6], and estimates its effect on perceived ease of use and perceived usefulness. Its novelty lies in foregrounding the dimensional structure of readiness, including the often-neglected inhibitor dimensions, in an underexamined creative population.

2. METHODS

2.1 Problem Identification and Formulation

The problem addressed in this study is that technology readiness, although widely regarded as an antecedent of AI adoption, is often measured superficially, either as a single variable or as disconnected dimensions, so that its internal structure and its strength as a driver of perceived ease of use and perceived usefulness remain unclear. The study therefore asks whether technology readiness, modeled as a higher-order construct, significantly affects perceived ease of use and perceived usefulness, how each dimension contributes to the readiness construct, and whether perceived ease of use mediates the effect of readiness on perceived usefulness.

2.2 Literature Review

Technology readiness refers to a person's general propensity to embrace and use new technologies to accomplish goals [3]. It is not about competence with a particular system but about an overall mental state produced by coexisting enablers and inhibitors. Optimism is a positive view that technology enhances control, flexibility, and efficiency; innovativeness is a tendency to be a technology pioneer. Working against these, discomfort is a perceived lack of control over technology, and insecurity is distrust of technology and skepticism about its ability to work properly [3], [4]. Because these four dimensions jointly manifest a single underlying disposition, technology readiness is appropriately represented as a higher-order construct that reflects all four [6], [15].

TRAM proposes that technology readiness operates as an antecedent of perceived ease of use and perceived usefulness [5], [6]. Individuals high in readiness approach new tools expecting them to be manageable and beneficial, which lowers the perceived effort of use and raises expectations of usefulness. The two constructs are also linked: within TAM, perceived ease of use is a well-established antecedent of perceived usefulness, because a tool that feels effortless is more readily seen as beneficial [5]. Empirical work across self-service kiosks, mobile learning, healthcare systems, digital payments, and AI adoption among teachers and entrepreneurs consistently shows that readiness positively influences perceived ease of use and perceived usefulness [7]-[12]. For digital creatives encountering AI tools, a ready disposition should similarly make the tools feel more approachable and, in turn, more valuable.

2.3 Development of Research Model and Hypotheses

Based on TRAM and TAM, technology readiness is expected to positively influence both perceived ease of use and perceived usefulness, and perceived ease of use is expected to raise perceived usefulness and to carry part of the effect of readiness. The following hypotheses are proposed:

H1. Technology readiness positively affects perceived ease of use of AI-based creative marketing tools.

H2. Technology readiness positively affects perceived usefulness of AI-based creative marketing tools.

H3. Perceived ease of use positively affects perceived usefulness of AI-based creative marketing tools.

H4. Perceived ease of use mediates the effect of technology readiness on perceived usefulness.

Because readiness is modeled as a second-order construct reflected by its four dimensions, the analysis also examines the relative contribution of each dimension to the readiness construct, providing a dimension-level view of what most defines readiness in this population. The research model is shown in Figure 1.

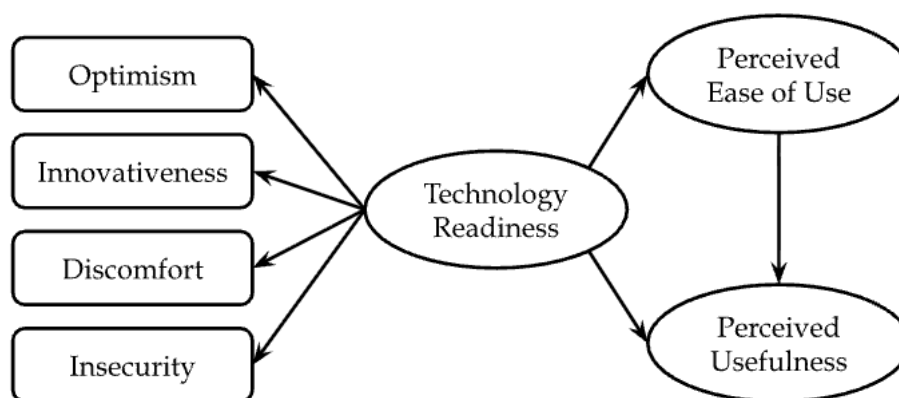


Figure 1. Research model with technology readiness as a second-order construct

2.4 Questionnaire Design

All constructs were measured with multi-item reflective indicators adapted from validated scales and rated on a five-point Likert scale (Table 1). Technology readiness was measured through its four TRI dimensions [3], [4]; perceived ease of use and perceived usefulness were

adapted from TAM instruments [5]. Inhibitor items (discomfort and insecurity) were reverse-coded so that higher values consistently indicate greater readiness. The operational definitions and sources of the constructs are summarized in Table 2.

Table 1. Likert scale

Score	Category	Description
5	Strongly Agree	The respondent strongly agrees with the statement
4	Agree	The respondent agrees with the statement
3	Neutral	The respondent has no clear opinion on the statement
2	Disagree	The respondent disagrees with the statement
1	Strongly Disagree	The respondent strongly disagrees with the statement

Table 2. Operational definition of constructs

Construct	Description	Source
Optimism	Positive view that AI tools enhance control, flexibility, and efficiency	Parasuraman (2000)
Innovativeness	Tendency to be a pioneer in trying new AI tools	Parasuraman (2000)
Discomfort	Perceived lack of control over and feeling overwhelmed by AI tools	Parasuraman (2000)
Insecurity	Distrust of AI tools and skepticism about their reliability	Parasuraman (2000)
Perceived Ease of Use	Degree to which using AI tools is expected to be effortless	Davis (1989); Lin, Shih & Sher (2007)
Perceived Usefulness	Degree to which AI tools are believed to enhance performance	Davis (1989); Lin, Shih & Sher (2007)

2.5 Pilot Test

A pilot test was conducted before the main data collection to assess the validity and reliability of the instrument. It was carried out in two stages, with 15 respondents in the first stage and 30 in the second, using purposive sampling of individuals experienced in documentation, publication, or digital marketing activities. The pilot analysis, performed in SPSS, led to the removal of three items (INN7, DIS8, and INS8), leaving 47 items for the main study.

2.6 Data Collection

The target population comprised Indonesian digital creative practitioners who use AI-based creative marketing tools, including graphic designers, content creators, videographers, social media strategists, digital marketers, and copywriters. Respondents were recruited through non-probability sampling combining purposive and snowball techniques, and the questionnaire was distributed online via a Google Form shared through social media platforms such as WhatsApp, Instagram, and TikTok. This procedure yielded 423 initial responses.

2.7 Data Analysis

The model was estimated using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4.1.1.8 [13], [14]. Technology readiness was specified as a second-order reflective construct using the repeated-indicators approach, in which the higher-order construct is measured by all indicators of its lower-order dimensions [6], [15]-[17]. During convergent-validity assessment, indicators with low loadings were removed iteratively, and the measurement model for this study retained 30 indicators across the six first-order constructs.

The measurement model was evaluated for convergent validity (outer loadings and average variance extracted), internal consistency (composite reliability and Cronbach alpha), and discriminant validity (heterotrait-monotrait ratio). Following guidance for higher-order constructs, the aggregate AVE of the second-order construct is not interpreted against the first-order threshold; its validity is judged from the significance and magnitude of the dimension loadings instead [15], [16].

2.8 Hypothesis Testing

The structural paths, the mediation effect, and the second-order dimension loadings were assessed via bootstrapping with 5,000 resamples using one-tailed tests, with a path considered significant when the t-value is at least 1.645 and the p-value is at most 0.05 [13]. Effect sizes (f-squared) were computed to gauge the practical strength of the paths, and the mediation was evaluated following the specific indirect-effects procedure [18].

3. RESULTS AND DISCUSSION

3.1 Pre-processing Data

Of the 423 responses initially collected, 3 respondents did not meet the eligibility criteria and were removed, leaving 420 responses for screening; no duplicate entries were found. In the completeness check, 22 respondents with one to three blank items were retained using mean imputation, while 1 respondent with five blank items was removed for exceeding the tolerance. In the consistency check, 64 respondents showing extreme response inconsistency (a range of four across three or more variables) were removed. In total, 68 responses were eliminated, resulting in a final sample of 355 respondents.

3.2 Respondent Characteristics

Table 3. Respondent characteristics (n = 355)

Characteristic	Category	n	%
Gender	Female	180	50.7
	Male	175	49.3
Age	< 20 years	19	5.4
	20-25 years	104	29.3
	26-30 years	129	36.3
	> 30 years	103	29.0
Profession	Graphic designer	80	22.5
	Content creator	72	20.3
	Videographer	60	16.9
	Social media strategist	57	16.1
	Digital marketer	48	13.5
	Copywriter	37	10.4
Experience	Corporate communication	1	0.3
	< 3 months	9	2.5
	< 6 months	37	10.5
	< 1 year	62	17.5
	1-3 years	109	30.8
	> 3 years	137	38.7

The final sample of 355 respondents was balanced by gender and dominated by practitioners in their productive years, most with substantial professional experience. Table 3 presents the respondent profile. Because multiple selections of AI tools were allowed, the total usage frequency exceeds the number of respondents; the most frequently used tools were Adobe Firefly (164), Canva AI (142), ChatGPT (111), Freepik AI (108), and Midjourney (101), indicating that practitioners combine several tools rather than rely on a single platform.

3.3 Data Analysis

Measurement model and the higher-order construct. All six first-order constructs demonstrated adequate reliability and convergent validity, with composite reliability above 0.80, Cronbach alpha above 0.70, and average variance extracted (AVE) at or above 0.50 (Table 4). Discriminant validity was supported, with the heterotrait-monotrait ratio between perceived ease of use and perceived usefulness, the highest among distinct constructs, at 0.735, well below the 0.90 threshold. The second-order technology readiness construct was reliable (composite reliability 0.883, Cronbach alpha 0.862). Following guidance for higher-order constructs, the aggregate AVE of the second-order construct (0.248) is not interpreted against the first-order 0.50 benchmark, because its indicators are the lower-order dimensions rather than individual items [15], [16].

Table 4. Reliability and convergent validity

Construct	Cronbach Alpha	CR	AVE
Optimism	0.808	0.862	0.512
Innovativeness	0.800	0.857	0.500
Discomfort (Reverse-Coded)	0.807	0.876	0.644
Insecurity (Reverse-Coded)	0.908	0.925	0.607
Perceived Ease Of Use	0.705	0.834	0.627
Perceived Usefulness	0.767	0.864	0.682
Technology Readiness (2nd Order)	0.862	0.883	N/A

The second-order loadings, reported in Table 5 and visualized in Figure 2, indicate how strongly each dimension represents technology readiness. All four loadings were positive and significant. The reverse-coded inhibitor dimensions carried the highest loadings, insecurity (0.762) and discomfort (0.652), followed by the enablers optimism (0.618) and innovativeness (0.549). This pattern suggests that, for these practitioners, readiness is defined at least as much by the absence of insecurity and discomfort as by the presence of optimism and innovativeness.

Table 5. Second-order loadings of technology readiness dimensions

Dimension	Loading	t-value	Decision
Insecurity (reverse-coded)	0.762	12.912	Significant
Discomfort (reverse-coded)	0.652	12.461	Significant
Optimism	0.618	9.456	Significant
Innovativeness	0.549	6.371	Significant

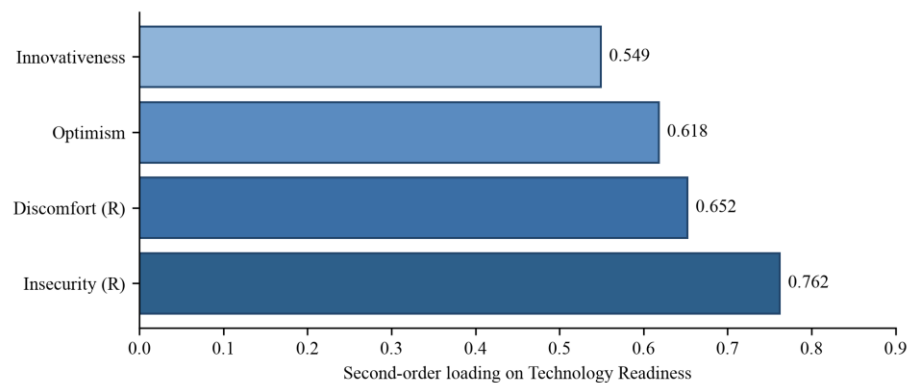


Figure 2. Relative contribution of dimensions to technology readiness

Structural model. Technology readiness significantly and positively affected perceived ease of use ($\beta = 0.388$, $t = 7.479$) and perceived usefulness ($\beta = 0.221$, $t = 4.084$), supporting H1 and H2, and perceived ease of use strongly affected perceived usefulness ($\beta = 0.485$, $t = 12.048$), supporting H3 (Table 6). The effect sizes were medium for perceived ease of use on perceived usefulness ($f\text{-squared} = 0.317$) and for readiness on ease of use ($f\text{-squared} = 0.177$), and small for readiness on usefulness ($f\text{-squared} = 0.066$). Technology readiness explained 15.0 percent of the variance in perceived ease of use ($R\text{-squared} = 0.150$), and readiness and ease of use together explained 36.8 percent of the variance in perceived usefulness ($R\text{-squared} = 0.368$).

Table 6. Structural paths

Hypothesis	Path	beta	t-value	f-squared	Decision
H1	TR -> PEOU	0.388	7.479	0.177	Supported
H2	TR -> PU	0.221	4.084	0.066	Supported
H3	PEOU -> PU	0.485	12.048	0.317	Supported

Mediation. The specific indirect effect of technology readiness on perceived usefulness through perceived ease of use was positive and significant ($\beta = 0.188$, $t = 6.564$), and the total effect of readiness on usefulness was 0.409 ($t = 7.327$). Because both the direct effect (H2) and the indirect effect are significant and point in the same direction, perceived ease of use partially (complementarily) mediates the relationship, supporting H4 (Table 7) [18]. All four hypotheses were therefore supported.

Table 7. Mediation analysis

Effect	Path	beta	t-value	Decision
Indirect	TR -> PEOU -> PU	0.188	6.564	Supported
Direct	TR -> PU	0.221	4.084	Significant
Total	TR -> PU	0.409	7.327	Significant

Discussion. The results provide a dimension-level answer to the research question. Modeled as a higher-order construct, technology readiness significantly drives both perceived ease of use and perceived usefulness, while perceived ease of use both responds to readiness and, in turn, raises perceived usefulness. This indicates that a favorable disposition toward technology chiefly reduces the perceived effort of adopting AI tools and, through that reduced effort, contributes to their perceived usefulness. The finding aligns with TRAM and with prior applications that position readiness as an upstream antecedent of perceived ease of use and perceived usefulness [6], [7], [10].

The most distinctive result concerns the inhibitor dimensions. Insecurity and discomfort, once reverse-coded, carried the highest loadings on readiness, implying that for digital creatives the reduction of distrust and unease is central to being ready for AI, not a peripheral concern. This is theoretically important because many studies drop inhibitor dimensions and thereby underrepresent readiness. Practically, it suggests that efforts to build AI readiness in the creative industry should directly address anxieties, such as fears about job displacement, data security, and loss of control, rather than focusing only on promoting enthusiasm and innovativeness. This finding is consistent with the respondent profile, in which visual-creative practitioners who routinely handle client data and original assets predominate.

This study draws on one part of a broader dataset on AI adoption among Indonesian digital creatives; a complementary analysis, examining how perceived ease of use and perceived usefulness carry the effect of technology readiness onward to behavioral intention, is reported separately.

CONCLUSION

This study examined technology readiness as a higher-order driver of the perceived ease of use and perceived usefulness underlying AI adoption among 355 Indonesian digital creatives. Modeled as a second-order reflective construct, technology readiness was reliably represented by its four dimensions and significantly increased both perceived ease of use and perceived usefulness, while perceived ease of use both responded to readiness and raised perceived usefulness, partially mediating the readiness-to-usefulness relationship. Notably, the reverse-coded inhibitor dimensions, insecurity and discomfort, contributed most to the readiness construct, underscoring that overcoming unease is as important as fostering optimism and innovativeness. Theoretically, the study affirms the value of modeling readiness as a multidimensional higher-order construct and highlights the neglected role of inhibitors; practically, it points to anxiety-reducing interventions as a route to greater AI readiness. Limitations include the cross-sectional, single-country design and the focus on perceived ease of use and perceived usefulness rather than actual usage; future research could test the dimensions across professions and generations and over time.

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