Artificial Intelligence (AI) Functions in an Integrated Technology Acceptance Model–Technology–Organization–Environment (TAM–TOE) Perspective on Micro Retailers' Willingness to Adopt in Tarlac City

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ABSTRACT

This study examined the willingness of registered micro retail enterprises in Tarlac City to adopt selected artificial intelligence (AI) functions using an integrated Technology Acceptance Model (TAM)–Technology–Organization–Environment (TOE) perspective. TAM constructs constitute the technological component of the analytical model, specifically perceived usefulness (PU) and perceived ease of use (PEOU). Organizational conditions consist of top management support, employee adaptability, and organizational preparedness, while environmental conditions are represented by business support and competitive pressure. Graphic design for advertising and business correspondence are retained as the practical AI application contexts rather than treated as latent predictors. Using a quantitative descriptive-correlational design and stratified random sampling, 115 valid responses from registered micro retail enterprises in Tarlac City comprised the final analytical sample. Descriptive findings showed favorable perceptions of AI usefulness and ease of use and a generally positive willingness to adopt AI functions. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used as the inferential framework because the analytical model contains multiple latent constructs and direct structural relationships. All measurement-model and structural-model results reported in this manuscript were based on the 115 valid responses. The revised model and manuscript therefore maintain conceptual and methodological consistency throughout the analysis.

Keywords: artificial intelligence, Technology Acceptance Model, Technology–Organization–Environment, micro retail enterprises, technology adoption, Tarlac City

INTRODUCTION

Artificial Intelligence (AI) has become an increasingly important technology for business operations, productivity, marketing, communication, and decision-making. Its applications are no longer limited to large enterprises; accessible AI tools are increasingly available to micro and small businesses for routine and promotional activities.

In micro retail enterprises, AI functions such as graphic design for advertising and business correspondence provide practical entry points because they can support marketing communication, content creation, customer interaction, and routine administrative work. However, adoption depends not only on the availability of AI tools but also on how business decision-makers perceive their usefulness and ease of use and whether the organization has sufficient internal capacity and environmental support.

The Technology Acceptance Model (TAM) developed by Davis (1989) identifies perceived usefulness (PU) and perceived ease of use (PEOU) as central beliefs associated with technology acceptance. In the present study, these constructs form the technological component of the analytical model. Because adoption by business organizations may also be shaped by internal organizational conditions and the external business

environment, the study extends the TAM perspective using selected dimensions of the Technology–Organization–Environment (TOE) framework.

The integration is made explicit to address the inconsistency identified during journal review. TAM is not treated as interchangeable with TOE. Instead, PU and PEOU represent the technological perceptions through which respondents evaluate AI, while organizational and environmental conditions are modeled as contextual extensions that may influence technological perceptions and adoption willingness. The two AI functions examined—graphic design for advertising and business correspondence—remain the practical application context and descriptive focus rather than separate latent predictors.

The study focuses on registered micro retail enterprises in Tarlac City. It contributes localized evidence on AI adoption among resource-constrained enterprises and provides a basis for business support, training, and digital-readiness interventions.

Statement of the Problem

1. How are the selected AI functions of micro retail enterprises described in terms of:

    1.1 graphic design for advertising
    1.2 business correspondence?

2. How do micro retail enterprises perceive AI integration in terms of:

    2.1 perceived usefulness
    2.2 perceived ease of use?

3. How is the willingness of micro retail enterprises to adopt AI functions described?

4. What are the relationships among the technological, organizational, environmental, and AI-adoption constructs in the integrated TAM–TOE model?

Hypothesis

H1: Technological perceptions (PU and PEOU) have a significant positive effect on willingness to adopt AI.

H2: Organizational conditions have a significant positive effect on technological perceptions.

H3: Organizational conditions have a significant positive effect on willingness to adopt AI.

H4: Environmental conditions have a significant effect on technological perceptions.

H5: Environmental conditions have a significant effect on willingness to adopt AI.

CONCEPTUAL AND ANALYTICAL FRAMEWORK

The study integrates the Technology Acceptance Model (TAM) with selected dimensions of the Technology–Organization–Environment (TOE) framework. TAM represents the technological dimension through perceived usefulness (PU) and perceived ease of use (PEOU), while the TOE framework incorporates organizational and environmental conditions that may influence technological perceptions and willingness to adopt AI. The AI functions of graphic design for advertising and business correspondence serve as the practical application contexts of the study.

The analytical framework examines the relationships among organizational factors, environmental factors, technological perceptions, and AI adoption. Organizational factors include top management support, employee adaptability, and organizational preparedness. Environmental factors include business support and competitive pressure. Technological perceptions are represented by perceived usefulness and perceived ease of use, while AI adoption is represented by the willingness of micro retail enterprises to adopt AI functions.

The proposed relationships are: organizational factors influence technological perceptions and AI adoption; environmental factors influence technological perceptions and AI adoption; and technological perceptions influence AI adoption. These relationships are examined using PLS-SEM to determine the significance and strength of the proposed paths.

RESEARCH METHODOLOGY

The study employed a quantitative descriptive-correlational research design. The population consisted of registered micro retail enterprises operating in Tarlac City based on the Business Permits and Licensing Office (BPLO) registry. Stratified random sampling was used to select the respondents.

A total of 120 questionnaires were distributed, of which 115 were retrieved, completed, and found valid for inclusion in the final analysis, yielding a response rate of 95.83%. Thus, the final analytical sample for all descriptive and PLS-SEM analyses was n = 115. The respondents were owners, managers, or key decision-makers of registered micro retail enterprises in Tarlac City.

The questionnaire consisted of sections covering the respondents' business profiles, technological perceptions in terms of perceived usefulness (PU) and perceived ease of use (PEOU), organizational factors in terms of top management support, employee adaptability, and organizational preparedness, environmental factors, and willingness to adopt AI. The items were measured using a four-point Likert scale ranging from 1 (Strongly Disagree) to 4 (Strongly Agree).

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to examine the relationships among the technological, organizational, environmental, and AI adoption constructs. The analysis included measurement-model assessment and structural-model assessment.

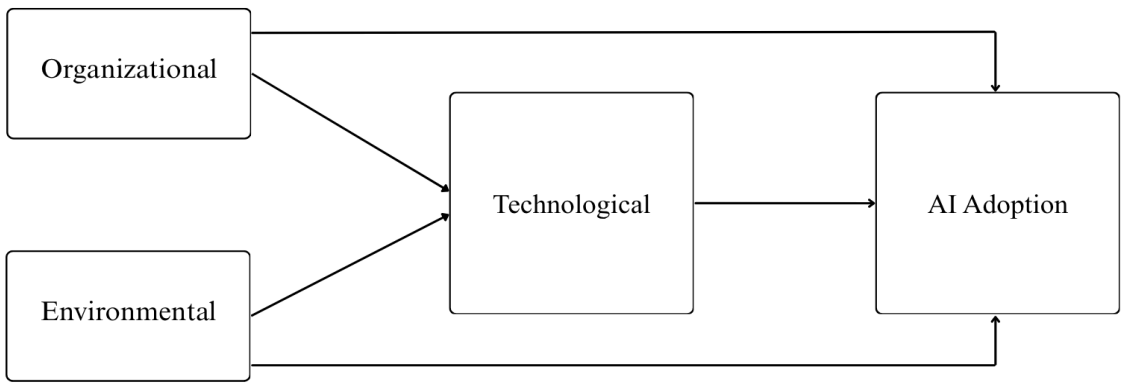
Measurement-Model Assessment

The measurement model was assessed in terms of indicator loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) for each latent construct. Convergent validity was evaluated based on indicator loadings and AVE, while discriminant validity was assessed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). The assessment was based on the 115 valid responses included in the study.

Structural-Model Assessment

The structural model was assessed using collinearity diagnostics through variance inflation factor (VIF), path coefficients (β), standard errors, t-values, p-values, coefficient of determination (R^2), and effect sizes (f^2), as applicable. Bootstrapping was employed to determine the significance of the hypothesized relationships, using a 0.05 level of significance.

Figure 1. Proposed Research Framework Integrating the TAM and TOE Frameworks



The study tested five hypothesized relationships among the Organizational, Environmental, Technological, and AI Adoption constructs. Specifically, the hypothesized paths examined were Organizational → Technological, Organizational → AI Adoption, Environmental → Technological, Environmental → AI Adoption, and Technological → AI Adoption. These relationships were evaluated using the 115 valid observations included in the analysis.

RESULTS AND DISCUSSION

AI Functions Used by Micro Retail Enterprises

The study examined two practical applications of artificial intelligence among micro retail enterprises: graphic design for advertising and business correspondence. These AI functions represent common business applications that support promotional activities and routine communication.

Graphic design for advertising includes the creation of posters, promotional materials, and social media content. Business correspondence involves the preparation, improvement, and management of routine business communications. These applications provide practical contexts for assessing the perceived usefulness, ease of use, and willingness of micro retail enterprises to adopt AI.

Table 2. Perceived Usefulness of AI

Indicator	Mean	SD	Description
AI can enhance the productivity of business operations.	2.7	0.85	Agree
Using AI can improve the quality of decision-making.	2.69	0.82	Agree
AI adoption will increase firm competitiveness.	2.77	0.79	Agree
Implementing AI can help reduce operational costs.	2.75	0.78	Agree
Composite Mean	**2.73**		**Agree**

The composite mean of 2.73 indicates that respondents generally agree that AI can provide useful business benefits. The results suggest favorable perceptions of AI in relation to productivity, decision-making, competitiveness, and operational cost reduction.

Table 3. Perceived Ease of Use of AI

Indicator	Mean	SD	Description
AI tools are user-friendly for business needs.	2.75	0.78	Agree
It would be easy for employees to learn how to use AI.	2.75	0.83	Agree
Interacting with AI systems does not require extensive technical skills.	2.81	0.83	Agree
The firm can easily integrate AI with existing systems.	2.65	0.85	Agree
Composite Mean	**2.74**		**Agree**

The composite mean of 2.74 indicates that respondents generally perceive AI functions as manageable and reasonably easy to use. The lowest mean concerns integration with existing systems, suggesting that ease of integration may remain an important practical consideration.

Willingness to Adopt AI Functions

Table 4. Willingness to Adopt AI Functions

Indicator	Mean	SD	Description
1. The firm is ready to adopt AI technologies in the near future.	2.9	0.83	Agree
2. The firm has already adopted AI technologies.	2.69	0.9	Agree

3. We plan to invest in AI-based tools or systems.	2.89	0.81	Agree
4. We have already invested in AI-based tools or systems.	2.67	0.91	Agree
5. Our management intends to include or improve AI in future strategic plans.	2.9	0.78	Agree
6. AI adoption will bring long-term benefits to our business.	2.94	0.81	Agree
Composite Mean	**2.83**		**Agree**

The composite mean is 2.83. The six item means range from 2.67 to 2.94, and all are interpreted as Agree under the four-point scale. The highest mean is 2.94 for the statement that AI adoption will bring long-term benefits, indicating favorable expectations regarding the long-term value of AI. The results demonstrate general willingness to adopt, although current investment and existing adoption remain comparatively lower than future-oriented intentions.

All PLS-SEM measurement-model and structural-model results reported below were generated using the 115 valid observations. The analysis reports reliability, convergent validity, discriminant validity, and structural-model statistics in accordance with the analytical framework.

Indicator loadings are reported alongside reliability and validity statistics. Discriminant validity is assessed using the Fornell–Larcker criterion and HTMT. Structural results report β, bootstrap mean, standard deviation, t-value, p-value, R^2, and f^2 as applicable.

Sample: n = 115. All measurement-model and structural-model analyses reported in this section were based on the 115 complete and valid responses included in the final dataset.

PLS-SEM MEASUREMENT AND STRUCTURAL RESULTS

Sample: n = 115. The analysis included 115 complete responses from the dataset.

Table 5. Measurement Model Assessment

Construct	Indicators	Cronbach's α	Composite Reliability	AVE
Technological	PU1–PU4; PEOU1–PEOU4	0.941	0.951	0.711
Organizational	TOPMGTSUPPORT1–3; EMP_ADAPTABILITY1–4; ORG_PREP1–3	0.956	0.962	0.718
Environmental	BOS_PS1–3; CP1–3	0.905	0.927	0.679
AI Adoption	AI ADOPTION1–6	0.939	0.952	0.769

The measurement model showed high internal consistency, with Cronbach's alpha values ranging from 0.905 to 0.956 and composite reliability values ranging from 0.927 to 0.962. The AVE values exceeded 0.50 for all constructs, indicating adequate convergent validity.

Table 6. Indicator Loadings

Construct	Indicator	Outer Loading
Technological	PU1	0.852
Technological	PU2	0.877
Technological	PU3	0.854
Technological	PU4	0.865
Technological	PEOU1	0.89
Technological	PEOU2	0.783
Technological	PEOU3	0.776

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Technological	PEOU4	0.842
Organizational	TOPMGTSUPPORT1	0.891
Organizational	TOPMGTSUPPORT2	0.844
Organizational	TOPMGTSUPPORT3	0.877
Organizational	EMP_ADAPTABILITY1	0.759
Organizational	EMP_ADAPTABILITY2	0.823
Organizational	EMP_ADAPTABILITY3	0.875
Organizational	EMP_ADAPTABILITY4	0.843
Organizational	ORG_PREP1	0.875
Organizational	ORG_PREP2	0.876
Organizational	ORG_PREP3	0.803
Environmental	BOS_PS1	0.869
Environmental	BOS_PS2	0.848
Environmental	BOS_PS3	0.792
Environmental	CP1	0.757
Environmental	CP2	0.822
Environmental	CP3	0.85
AI Adoption	AI ADOPTION1	0.831
AI Adoption	AI ADOPTION2	0.862
AI Adoption	AI ADOPTION3	0.916
AI Adoption	AI ADOPTION4	0.844
AI Adoption	AI ADOPTION5	0.905
AI Adoption	AI ADOPTION6	0.9

Table 7. Discriminant Validity Using the Fornell–Larcker Criterion

Construct	Technological	Organizational	Environmental	AI Adoption
Technological	0.843	0.844	0.841	0.807
Organizational	0.844	0.848	0.899	0.828
Environmental	0.841	0.899	0.824	0.828
AI Adoption	0.807	0.828	0.828	0.877

The Fornell–Larcker results indicate that the square root of AVE exceeds the inter-construct correlations for most construct pairs. However, the Organizational–Environmental pair shows a high correlation (r = 0.899), indicating limited discriminant separation between these constructs.

Table 8. Heterotrait–Monotrait (HTMT) Ratio

Construct	Technological	Organizational	Environmental	AI Adoption
Technological	—	0.883	0.91	0.857
Organizational	0.883	—	0.966	0.868
Environmental	0.91	0.966	—	0.896
AI Adoption	0.857	0.868	0.896	—

The HTMT results show values below 0.90 for most construct pairs. The Technological–Environmental ratio (0.910) and Organizational–Environmental ratio (0.966) exceed the commonly used 0.90 threshold, indicating potential discriminant-validity concerns involving the Environmental construct. These results are therefore

interpreted with caution when distinguishing the Environmental construct from the Technological and Organizational constructs.

Table 9. Structural Model Results

Hypothesis	Structural Path	β	Bootstrap Mean	STDEV	t-value	p-value	Decision
H1	Technological → AI Adoption	0.284	0.257	0.204	1.389	0.165	Not Supported
H2	Organizational → Technological	0.456	0.458	0.13	3.519	< .001	Supported
H3	Organizational → AI Adoption	0.309	0.32	0.137	2.252	0.024	Supported
H4	Environmental → Technological	0.431	0.431	0.132	3.269	0.001	Supported
H5	Environmental → AI Adoption	0.311	0.328	0.159	1.951	0.051	Not Supported

Bootstrapping with 2,000 resamples was used to assess the significance of the structural paths at the 0.05 level. Organizational factors significantly predicted technological perceptions and AI adoption, while environmental factors significantly predicted technological perceptions but did not have a statistically significant direct effect on AI adoption. The direct effect of technological perceptions on AI adoption was not statistically significant in the n = 115 analysis.

Table 10. Collinearity, Explanatory Power, and Effect Size

Endogenous Construct	Predictor	VIF	R^2	f^2
Technological	Organizational	5.202	0.748	0.158
Technological	Environmental	5.202		0.142
AI Adoption	Technological	3.964	0.743	0.079
AI Adoption	Organizational	6.026		0.062
AI Adoption	Environmental	5.94		0.063

The R^2 values indicate that the model explains 74.8% of the variance in Technological perceptions and 74.3% of the variance in AI Adoption. VIF values ranged from 3.964 to 6.026. Effect sizes ranged from 0.062 to 0.158, indicating small to moderate effects.

CONCLUSION

The study examines AI adoption among micro retail enterprises using an integrated TAM–TOE perspective. Perceived usefulness and perceived ease of use represent the technological dimension, while organizational and environmental conditions represent factors associated with AI adoption. Graphic design for advertising and business correspondence serve as the practical AI application contexts of the study.

Based on the descriptive results from the 115 valid respondents, micro retail enterprises in Tarlac City generally perceive AI as useful and easy to use and demonstrate willingness to adopt AI functions. The overall composite mean for willingness to adopt AI is 2.83, indicating agreement among the respondents. The PLS-SEM results based on the 115 valid responses provide evidence on the relationships among the technological, organizational, environmental, and AI adoption constructs.

RECOMMENDATIONS

Micro retail enterprises may prioritize practical AI applications in graphic design for advertising and business

correspondence because these functions provide accessible entry points for AI use.

Business owners and managers may strengthen internal digital readiness through employee training, management support, and organizational planning before expanding AI use.

Government agencies, local government, academic institutions, and business-support organizations may provide practical AI literacy, technical assistance, and affordable access to appropriate digital tools.

Technology providers may develop user-friendly and low-cost AI solutions suitable for micro enterprises with limited financial and technical resources.

Future researchers may replicate the integrated TAM–TOE model in other Philippine cities and sectors and may examine actual post-adoption outcomes in addition to willingness to adopt.

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