Bridging Theory and Practice: Introducing the Heterogeneous Technology Acceptance Model (H-TAM) for Practical Market Research and Product Comparison

Pawel Robert Smolinski
University of Gdansk / Faculty of Economics
Sopot, Poland *pawel.smolinski@ug.edu.pl*

Jacek Winiarski
University of Gdansk / Faculty of Economics
Sopot, Poland *jacek.winiarski@ug.edu.pl*

Abstract

This paper examines the evolution and limitations of traditional acceptance models, notably the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These models have been valuable frameworks for IS researchers; however, their limited explanatory power and rigid methodology have constrained their applicability in practical business contexts. To address this challenge, we propose the Heterogeneous Technology Acceptance Model (H-TAM), a practitioner-oriented framework that leverages established IS theory for real-world market and product research applications. Central to this framework are Impact Scores, which quantify a product's relative performance on technology acceptance variables compared to market benchmarks and competitors. We use simulated data to illustrate how H-TAM captures differences in user acceptance across technology products. The Impact Scores can then be used to inform practitioner decision-making in market analysis and product development. This framework advances the practical utility of technology acceptance theory and offers a foundation for more context-sensitive research and applications.

Keywords: Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), market research in technology, business research

1. Introduction

Technology acceptance is a concept in information science that explains how and why users adopt or reject technological innovations. The study of technology acceptance draws from multiple disciplines, including information systems, human-computer interaction, product design, management and economics [5, 18, 31]. Its primary goal is to identify the factors that influence technology adoption. However, interest in the field has recently declined due to criticism of models like TAM and UTAUT, which, despite their theoretical contributions, often fail to predict real-world user behavior and lack generalizability across contexts [27, 31]. Scholars also note a sense of theoretical saturation, where further refinements offer diminishing theoretical returns [4, 25, 24].

We argue that this decline stems from viewing technology acceptance as a static concept. Reconceptualizing acceptance as a dynamic, context-dependent phenomenon can restore the field's relevance. Instead of multiplying constructs and models, scholars need tools that make existing models sensitive to contextual heterogeneity and, in turn, useful for market research and product design.

This study introduces the Heterogeneous Technology Acceptance Model (H-TAM), a multilevel framework that estimates how predictor effects vary across usage contexts. H-TAM addresses three questions that earlier acceptance studies overlook:

RQ1: Do acceptance predictors exhibit significant cross-context variation?
RQ2: What does this heterogeneity reveal about the nature of technology acceptance as a context-dependent phenomenon?

RQ3: How can these variations be translated into business and economic insights?

Using a simulated market-research scenario, we demonstrate that H-TAM answers these questions and generates new insights absent from traditional, context-agnostic acceptance models.

2. Literature Review

2.1. Historical Context

The origins of technology acceptance research trace back to Ajzen's Theory of Reasoned Action (TRA) and Theory of Planned Behavior (TPB) [2, 3]. These theories laid the foundation for modeling the relationship between attitude and technology use. A more technology-specific approach emerged with Davis's Technology Acceptance Model (TAM), which identified Perceived Usefulness (PU) and Perceived Ease of Use (EU) as key predictors of user acceptance [13]. TAM's generality allowed broad application across various technologies, establishing it as a foundational model.

As technologies grew more complex, refinements to TAM emerged, leading to multiple extended models [1, 4, 14, 35]. To unify these developments, the Unified Theory of Acceptance and Use of Technology (UTAUT) was proposed, integrating key constructs such as Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions [36]. Although UTAUT was designed to unify the fragmented landscape of acceptance models, the field still continued its pattern of refinement and extension. This trend shifted attention from practical applications, which UTAUT was meant to facilitate, toward a continuous cycle of theoretical model-building, resulting in numerous TAM+ and UTAUT+ variants [4]. Consequently, the practical relevance of technology acceptance research was being overshadowed by an emphasis on theoretical perfection.

2.2. Practical Applications Of Technology Acceptance Research

This theoretical proliferation has distanced the field from its original purpose. Reflecting on Davis's definition of technology acceptance as the willingness of users to accept and use available systems [13], it becomes clear that research has mainly focused on expanding predictors like Perceived Usefulness (PU). However, we must critically assess what practical application arises from knowing that factors such as PU are significant predictors of a user's willingness. Does this knowledge extend beyond the tautological observation that technologies perceived as useful are used by users [4]. This conceptualization risks reducing technology acceptance to a statement of the obvious, albeit articulated with a more sophisticated vocabulary. The value of technology acceptance research, therefore, should be measured not just by its theoretical sophistication but by its capacity to address real world problems. Criticism of the limited practical relevance of technology acceptance research is well-established [4, 24, 27, 28, 31, 33]. In response to these critiques, there has been a shift towards more practically oriented applications of technology acceptance frameworks. Recent efforts, like applying TAM to product design, identifying user barriers, and integrating TAM variables into SWOT analyses, show progress in this direction [12, 30, 31]. Nevertheless, a persistent obstacle remains: the false assumption that technology acceptance models are fixed and unchanging.

2.3. The Fixed Assumption

The fixed assumption suggests that once predictors like Perceived Usefulness (PU) are repeatedly validated, their role is fully understood, making further research unnecessary unless new variables are introduced [9, 17, 19]. However, this assumption ignores the variability in technology acceptance and its predictors. The problem is not in the significance of a predictor's effect, but in its effect size. Effect size refers to the magnitude of the relationship between a predictor and an outcome. It quantifies the practical significance of a finding [16]. It is not merely whether a predictor is statistically significant, but how strongly it influences the outcome that matters [1]. Recognizing this undermines the fixed perspective and underscores the need to explore variability in technology acceptance.

For instance, a study on e-learning software acceptance [32] showed that while both academic and elementary school teachers valued Performance and Effort Expectancy, the effect sizes differed: academic teachers prioritized functionality, while school teachers valued ease of use. Such differences offer practical insights for fields like product design and market research. Focusing on heterogeneity in predictor effect sizes across contexts can yield more meaningful findings beyond theoretical model validation.

2.4. Evidence For Heterogeneity In Technology Acceptance Models

Heterogeneity in technology acceptance predictors has been documented through two main research approaches: comparative studies and meta-analyses. Comparative studies examine how acceptance models perform across different contexts and consistently demonstrate that significant differences in effect sizes exist across settings [23, 31, 32]. For example, Facebook and Twitter differ on relevant model attributes, yet treating them as a single social media category creates misleading impressions of uniform predictor significance across platforms [23]. Similarly, meta-analyses of technology acceptance research consistently validate core predictors like Perceived Usefulness and Ease of Use as significant, yet they also reveal significant variability in effect sizes between different contexts [6, 15, 22]. This demonstrates that, while some factors are universally important, their influence on user behavior varies considerably across contexts, challenging the fixed assumption.

3. Utilizing Model Heterogeneity

Comparative studies emerged as a potent approach to derive value from the heterogeneity in effect sizes. These studies involve identifying different contexts where acceptance may vary - such as distinct user groups or contrasting IT products. The aim is to compare the effect sizes of model parameters between these contexts. While parameters are usually significant across contexts, their effect sizes most often differ [31]. In comparing technologies, parameter effect sizes can inform market analyses, like SWOT analysis, where technology acceptance variables highlight comparative advantages [12]. For instance, a study might reveal Facebook's comparative advantage in user immersion over Twitter, guiding developers in prioritizing this feature [23]. When developers know that improving one feature will have a larger effect in their specific context than improving other features, they can allocate resources more strategically. This context-sensitive approach transforms abstract theoretical constructs into concrete business strategy.

3.1. Investigating Differences In Effect Sizes: Methods And Considerations

Investigating the difference between model parameters and their effect sizes is a critical aspect of comparative technology acceptance research. We compare the effect sizes across different contexts, as this can reveal competitive advantages of various technology products. This process entails inferring whether the differences in effect sizes, such as those in Perceived Usefulness, across various contexts, are substantial enough to be considered meaningful and not merely the result of random variation.

Inferring the significance of the difference in effect sizes between two parameters is more complex than assessing the significance of a single parameter [11]. Initially, model specification must be considered. Variations in specifications, such as differing sets of predictors or interaction terms, can influence a parameter's effect size. To ensure meaningful comparisons, the model specifications being compared must align. Yet, even within the same model, the underlying assumptions, such as normality of residuals and homoscedasticity, must hold true in both contexts; any violation can compromise the reliability of the estimates and their comparisons. If the assumptions are satisfied, a common method for testing coefficient differences is the Z-test, where a calculated Z-score is used to derive a p-value from the standard normal distribution [11]. A p-value below a typical threshold (e.g., 0.05) indicates statistical significance in the difference. In scenarios where pooling data is more feasible, introducing a context indicator variable and an interaction term between this indicator and the independent variable can also be effective. The interaction coefficient then tests for differences in slopes between contexts. In cases where Z-test assumptions are not fully met or the structural model is complex, bootstrapping might offer a robust alternative.

For complex models, where pooling is not feasible, structural invariance testing is a comprehensive method to investigate parameter differences between contexts [26]. However, extending comparisons to three or more groups leads to the statistical issue of multiple tests. Adjusting for multiple comparisons is an appropriate solution, but it increases p-value thresholds and reduces sensitivity of tests. While structural invariance analysis and bootstrapping can assist in multiple context comparisons, their usefulness decreases with increasing number of groups (exceeding ten).

3.2. Mixed-effects Models as a Solution for Context Variability Inference

The challenges presented by traditional methods of inferring the significance of effect size differences across contexts can be circumvented by employing mixed-effects models. The mixed-effect models handle the variance in model parameters between contexts by introducing random effect parameters [21]. This approach is suitable when dealing with many groups (more than ten), as it allows for the estimation of variance parameters that capture the heterogeneity across different contexts. Mixed-effects models provide a tool for structured analysis, accommodating the variability among context-specific estimates without the restrictive assumptions of homogeneity required by conventional methods. In the subsequent section, we will discuss how mixed-effects models can be conceptualized as a new framework for technology acceptance research.

4. The Heterogeneous Technology Acceptance Model (H-TAM)

The Heterogeneous Technology Acceptance Model (H-TAM) represents a new advancement from traditional Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT). Rather than proposing yet another model with predetermined variables, H-TAM introduces a flexible framework. Unlike traditional acceptance models that prescribe specific variables (such as PU or EU), H-TAM operates as a meta-framework within which any acceptance model can be specified and analyzed. The framework's true innovation lies not in identifying new predictors of technology acceptance, but in systematically quantifying how the effects of any chosen predictors differ across contexts. Whether researchers include traditional TAM/UTAUT variables or context-specific factors like price, immersive experience, or cultural influences, H-TAM's primary contribution is its ability to capture and quantify the heterogeneity in these effects across different user groups, technologies, or environments [25]. This context-centric approach transforms how we understand technology acceptance. Traditional models implicitly assume that predictor effects are fixed across contexts. H-TAM explicitly assumes that predictor effects vary across contexts and these context-driven variations are its central feature. This focus shift enables researchers and practitioners to move beyond questions of „what predicts acceptance?" to inquiries about „how does acceptance changes across different contexts?"

These basic assumptions of H-TAM can be expressed in a general model equation as follows:

$$Acceptance = (\beta_0 + u_{0i}) + \sum_{k=1}^{p}(\beta_k + u_{ki}) \times X_{ki} + \epsilon_i \tag{1}$$

Where:

- β_0 is the intercept for the model,
- u_{0i} is the context effect for the intercept in context *i,*
- β_k are the fixed effect coefficients for predictor *k* (averaged across all contexts),
- u_{ki} are the context effects for predictor *k* in context *i*,

- X_{ki} represents the k^{th} predictor in context i (this can be any predictor - whether traditional TAM/UTAUT variables like Perceived Usefulness, or context-specific variables like price, cultural factors, etc.),
- p is the number of predictors (attributes),
- ϵ_i is the error term for context *i.*

The predictors X_{ki} can represent any theoretically or empirically justified variables, including traditional TAM variables (Perceived Usefulness, Perceived Ease of Use), UTAUT variables (Performance Expectancy, Effort Expectancy, Social Influence), context-specific factors (price, cultural variables, technology characteristics), user demographics, or any other relevant predictors.

The H-TAM equation is a systematic decomposition of all predictor effects into fixed effects and context effects. The fixed effects (β_k) correspond to the average influence of predictors across all contexts (similar to traditional model coefficients). The context effects (u_{ki}) quantify the deviation of these influences within specific contexts. Importantly, H-TAM does not prescribe which variables researchers should include. Instead, it provides a framework to understand how any chosen variables perform differently across contexts. This flexibility means that H-TAM is not competing with existing models by proposing alternative predictors, but rather offering a new lens through which any technology acceptance model can be examined. For robust estimation of these context effects, sufficient context units (ideally ten or more) are required. When context units are limited, alternative methodologies such as structural invariance analysis may be employed (see Investigating Differences In Effect Sizes: Methods And Considerations section).

The estimation of H-TAM's parameters is based on mixed-effect modeling. These models offer the advantage of fitting the H-TAM equation directly to the data. These models can be estimated using Markov Chain Monte Carlo algorithms [7]. MCMC provides a statistical machinery necessary to capture the complex heterogeneity that H-TAM seeks to estimate. For more detailed discussion on model fitting, see the Supplementary Materials.

5. Simulation study

To demonstrate H-TAM in practice, we simulate an example that can be applied to any technology market with competing products.

Consider a scenario where we are a market research firm aiming to study technology acceptance across competing products. The market consists of multiple offerings designed to fulfill similar purposes (e.g., e-learning software facilitating online education or streaming services providing entertainment content). The user's decision to adopt a particular technology (acceptance) is determined by core predictors of technology acceptance, such as Perceived Usefulness (PU) or Ease of Use (EU), but also by context-specific factors. These context-specific predictors can vary by domain (for e-learning software, they might include Price Attractiveness (PA) or Integration (Int) and for streaming services, they might include Content Library (CL) etc.). From the H-TAM, we can expect the effect size of these predictors to vary among different products within each category, expressed through context effect coefficients. H-TAM accounts for this variability and allows us to analyze if certain products have advantages over others in their respective markets.

The fixed effect for the model parameter can be conceptualized as the expected market trend, representing an average effect across all products. A substantial context effect then indicates that individual effect sizes of acceptance predictors significantly deviate from this expected market trend. Products with effect sizes above the market trend can be considered as having market advantage. For instance, if Product A has a PU effect substantially exceeding the market trend, it implies that its users highly value its usefulness. Even minor improvements in its usefulness could result in substantial increases in acceptance. Conversely, Product B might have a PU effect size below market trend, indicating underperformance and a lack of translation of its usefulness into user acceptance. In this context, Product A holds a competitive edge over Product B, as its usefulness has a stronger correlation with higher user acceptance.

Besides the effect sizes of predictors, there is a second metric - the predictor mean, which has been overlooked in technology acceptance research. This metric is important when applying H-TAM to market research. The predictor mean indicates the current extent to which a technology product meets users' expectations. For example, if a product has a higher PU mean than the market PU average, it suggests that users perceive it as more useful compared to other market options. Furthermore, if PU has a large effect size, it indicates that the product is not only seen as more useful by users compared to its market counterparts, but that this perception significantly contributes to increased acceptance. These two metrics, when used together, provide measures for analyzing the competitiveness of the technology market using H-TAM. We will now illustrate this analysis with simulated data.

5.1. Data Simulation

In our simulation, we aimed to replicate typical patterns observed in technology acceptance research rather than generate specific model values. Technology acceptance studies often use psychometric questionnaires with Likert scales (1-7) and exhibit a skew toward higher rating. Traditionally designed for fixed-effect models like TAM, these studies usually analyze a single product. In contrast, our mixed-effect approach required a nested structure with multiple products and their users.

We simulated 800 users evaluating 20 products, totaling 16,000 observations. This can be interpreted as either different groups of 800 users per product or one group assessing all products. This approach reflects the data structure commonly used in previous technology acceptance research [23, 32]. For simplicity, we assumed each participant evaluated all products, without missing data.

Our H-TAM simulation included two core predictors (Perceived Usefulness and Ease of Use) and two context-specific predictors (Price Attractiveness and Integration). Responses were generated via truncated normal distributions (1-7 range) with mean shifts to reflect typical positive skewness. We generated fixed and random effects using an artificial covariance structure designed to ensure positive product-specific effects.

Finally, we simulated the Behavioral Intention (BI) variable, representing user willingness to use a product and fitted a mixed-effect model using the brms package in R [7]. Full simulation details and code are provided in the Supplementary Materials.

6. Results

The results of the H-TAM estimation are detailed in Table 1. Our analysis reveals the anticipated outcomes: all fixed effects are significant. The core TAM predictors - Perceived Usefulness (PU) and Ease of Use (EU) - have the largest fixed effect sizes among all predictors. This finding reinforces a well-established conclusion in technology acceptance research: products perceived as useful and easy to use are more likely to be accepted by users. In addition to these core predictors, the model also included two context-specific predictors: Price Attractiveness and Integration. Both showed significant fixed effects. However, their effect sizes are smaller than those of PU and EU, indicating a lesser, yet still important, impact on users' willingness to use a product.

The fixed effects are typical of those found in technology acceptance studies. The innovation of H-TAM is highlighted in context effects. The second part of Table 1 indicates that all context effect coefficients, along with their confidence intervals, exceed zero. This indicates significant variability in the effect sizes of fixed coefficients across different products. The greater the context effect, the more pronounced this variability becomes between products. PU exhibits the largest context effect of all variables. It indicates that PU's impact on Behavioral Intention (BI) varies substantially across different products. Conversely, the context effect for Price Attractiveness is the smallest, indicating that product-specific coefficients for Price Attractiveness are relatively consistent with the fixed effect coefficient, i.e., there is less variance.

Table 1. H-TAM Model Estimation Results

Parameters	Estimate	*SE*	95% Bayesian CI	
			LL	*UL*
Fixed effects				
Intercept	2.21	.85	.51	3.85
Perceived Usefulness	1.94	.18	1.56	2.30
Ease of Use	1.31	.09	1.13	1.47
Price Attractiveness	.91	.04	.83	.98
Integration	.83	.05	.74	.92
Context effects				
Intercept	3.84	.69	2.75	5.44
Perceived Usefulness	.85	.16	.61	1.21
Ease of Use	.39	.07	.27	.56
Price Attractiveness	.17	.03	.11	.24
Integration	.21	.04	.14	.30

H-TAM's analytical capabilities extend to examining product-specific effects and means, which represent the model's estimates for individual products. Table 2 showcases these estimates for Perceived Usefulness (PU) and Ease of Use (EU), the two predictors with the largest context effect. From Table 2, we can see that product 18 demonstrates the largest effect size for PU. It indicates that for this product, usefulness has a considerably stronger impact on user acceptance than is expected based on the fixed effect and observed for other products. However, product 18 also ranks lower in actual usefulness as assessed by its users, falling below the grand mean usefulness for all products. This observation suggests that although the product usefulness is extremely important for users, the product itself has not yet fully met users' expectations, highlighting an opportunity for improvement. Consequently, we can expect that improvements in product 18 usefulness will greatly increase product acceptance. Product 10 also shows a relatively large PU effect size, but unlike product 18, users evaluate it as more useful than other products on the market. This indicates that product 10 not only has a significant advantage in Perceived Usefulness but also effectively leverages this feature to gain user acceptance. Its high usefulness directly and strongly correlates with higher user acceptance, demonstrating a successful alignment of product features with user expectations.

Table 2. H-TAM Product-Specific Effects, Means, and Impact Scores for PU and EU predictors

Product	Product-specific effect		Product-specific mean		Product impact score	
	PU	*EU*	*PU*	*EU*	*PU*	*EU*
1	1.81	**1.04†**	4.99	**2.74†**	.47	**−1.87†**
2	1.42	1.26	3.84	3.01	−1.24	−.95
3	2.25	1.05	5.34	3.48	1.41	−.91
4	**1.30†**	1.38	**5.52***	3.43	.52	−.13
5	1.45	1.11	4.06	**5.42***	−1.05	**1.68***
6	1.62	**1.62***	3.94	3.82	**−1.00†**	.97
7	2.47	1.46	4.66	3.99	.86	.81
8	**1.34†**	**1.04†**	**3.59†**	**4.87***	**−1.77†**	.81
9	1.40	1.42	3.84	3.79	−1.40	.42
10	**2.76***	**2.42***	5.22	3.32	**1.86***	**2.41***
11	1.76	1.07	**3.65†**	**2.78†**	−1.19	**−1.73†**
12	**2.63***	1.11	5.07	**4.94***	1.54	1.08
13	**1.31†**	1.22	3.79	3.60	**−1.56†**	−.31
14	1.50	1.45	4.40	3.25	−.59	−.17
15	2.50	**1.55***	**5.39***	4.21	1.76	**1.28***
16	2.07	1.50	3.76	2.97	**−.69†**	−.38
17	1.34	1.09	**3.63†**	**2.94†**	**−1.71†**	**−1.86†**
18	**4.25***	1.36	3.85	2.87	**1.98***	−.88
19	1.53	1.05	3.99	4.59	−1.07	.50
20	2.19	**0.98†**	**6.57***	3.56	**2.82***	−.98

Note. Product-specific effect represents the magnitude of influence that PU and EU have on user acceptance for each product. Product-specific mean indicates the average user rating for PU and EU per product, and the product Impact Score combines these two metrics to provide an overall assessment of the product's performance against market trends. Asterisks (*) identify the top three performing products in terms of product-specific effects or product Impact Scores. Daggers (†) highlight the three products with the lowest scores, signaling areas for potential improvement to meet market standards.

These conclusions are further supported by Figure 1, which graphically displays all products in terms of their product-specific effects (plotted on the x-axis) and product-specific means (y-axis). The vertical dotted line in the figure represents the fixed effect and serves as a benchmark for the average effect a variable is expected to have on Behavioral Intention (BI) in the market. Products positioned to the right of the vertical line exhibit product-specific effects that surpass the market average, with their distance from the line indicating the degree of this advantage. Conversely, products on the left side are performing below market expectations, indicating that their features do not translate into acceptance as expected. Similarly, the horizontal line represents the grand mean and we can analogously interpret it as a market effect. Products located above or below this line are perceived by users as better or worse than the market average in terms of that specific variable. The further their position from this line, the stronger their perceived advantage or disadvantage.

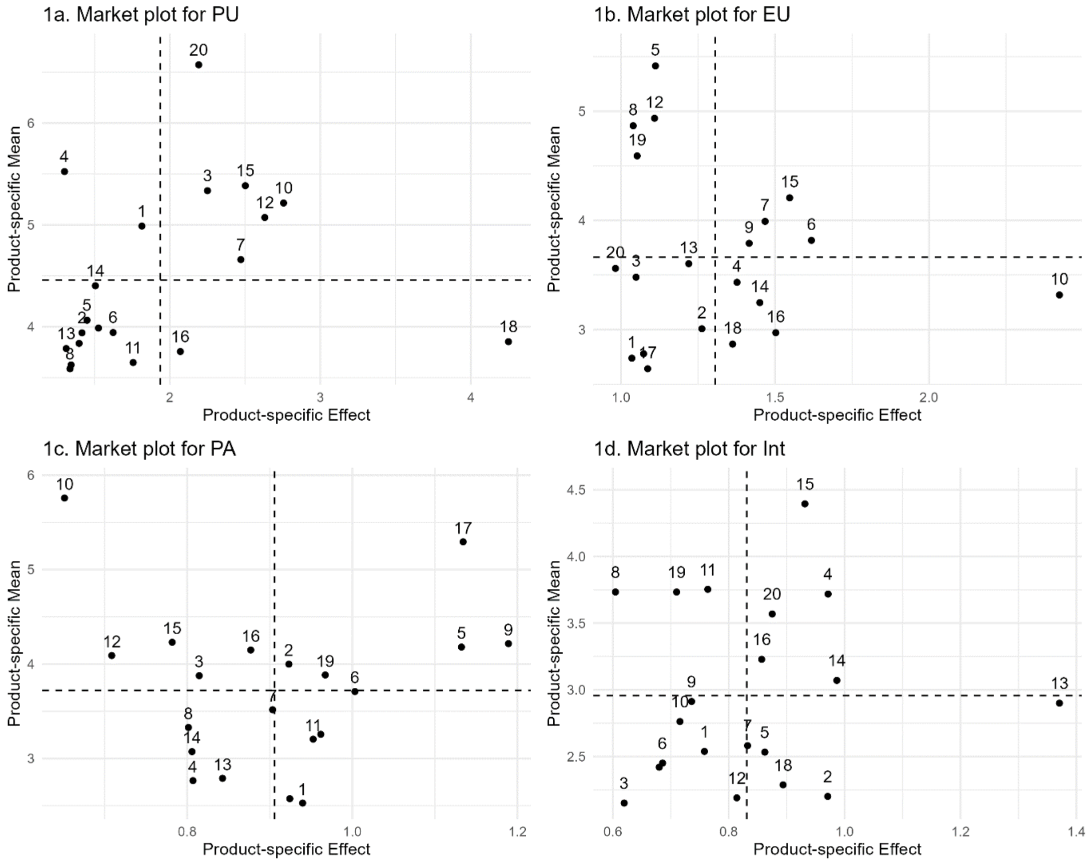

Fig. 1. Market Positioning of Products Based on Specific Attributes in the H-TAM Model

Zooming on Figure 1a, which illustrates product-specific effects for PU, we observe that the vertical line represents the fixed effect from Table 1, approximately 1.95. Most products cluster around this value, but significant variation exists, with some products distant from this line. Notably, products 18 and 10, identified in Table 2 as having the largest effect size of PU on acceptance, stand out as being the farthest from the vertical line. This variation underscores the strength of the context effect, especially evident in the dispersion of product-specific effects along the x-axis. For PU, this range extends from a low of 1.31 (product 13) to a high of 4.25 (product 18). For other variables like Price Attractiveness and Integration, context effects are comparatively smaller, as evidenced by the lesser dispersion of product-specific effects around the vertical line.

The same rationale applies to the analysis of product-specific means and the grand mean (horizontal line). In the case of product 20, as shown in Figure 1a, it has one of the highest product-specific PU means, signifying its exceptional Perceived Usefulness, above the market average and other products. In contrast, product 8 has the lowest product-specific mean, indicating that users perceive it as less useful compared to market standards.

6.1. Impact Scores

We can further leverage the variance in predictors and means to devise a single Impact Score (IS) that indicates a product's relative position against market expectations. Impact Score synthesizes all metrics from the H-TAM model into a singular score. It offers analysts a clear metric for evaluating a product's performance in specific attribute, such as Ease of Use. The mathematical concept behind the Impact Score is delineated in equation 2.

For each product *i* and each predictor *k*, the product Impact Score $IS_{i,j}$ is calculated as:

$$IS_{i,j} = \left(\frac{w_{ik} - \beta_k^{market}}{u_k^{w^{market}}}\right) + \left(\frac{m_{ik} - M_k^{market}}{\sigma_k^{M^{market}}}\right) \quad (2)$$

Where:

- w_{ik} is the product-specific effect of predictor k for product i,
- m_{ik} is the product-specific mean of predictor k for product i,
- β_k^{market} and M_k^{market} are the fixed effect and grand mean for predictor k, respectively,
- u_k^{market} and σ_k^{market} are the context effect and the standard deviation of the grand mean of predictor k, respectively.

This equation has two parts:

1. Effect Impact: $\left(\frac{w_{ik} - \beta_k^{market}}{u_k^{w^{market}}}\right)$ calculates the deviation of the product-specific effect i for a predictor k from the fixed effect (effect expected by the market) scaled by the context effect.
2. Mean Impact: $\left(\frac{m_{ik} - M_k^{market}}{\sigma_k^{M^{market}}}\right)$ calculates the deviation of the product-specific mean i for a predictor k from the grand mean (market mean) scaled by the grand standard deviation.

Impact scores are based on the statistical concept of standard scores. Standard scores measure how far a data point is from a central value, normalized by a scale factor. Our definition of Impact Scores includes standard scores for both the effect size (termed Effect Impact) and product means (termed Mean Effect). Each standard score reflects the relative position of each product within the market, based on the selected metric (central value) and its variability (scale factor). We assume that these two scores, Effect and Mean Impact, hold equal significance in determining a product's competitiveness. It implies that the influence of the model predictor on acceptance and the average user perception (its mean) are both equally important in determining the product's market position. This equal weighting is quantitatively represented in Equation 2, where the Impact Score is calculated as the sum of these two scores. Given this operationalization, a high positive $IS_{i,k}$ indicates that the product *i* significantly surpasses market trends in the attribute *k*, considering both its product-specific effect and mean. Conversely, a high negative score indicates that the product falls short of market trends. A $IS_{i,k} = 0$ means that the product's feature is perfectly aligned with the market.

The final two columns of Table 2 display the calculated Impact scores for Perceived Usefulness (PU) and Ease of Use (EU). For example, product 10 achieves one of the highest Impact Scores in both features ($IS_{10,PU} = 1.86$ and $IS_{10,EU} = 2.41$). This finding aligns with observations from Figures 1a and 1b, where Product 10's metrics consistently exceed market expectations, except for the product-specific mean for EU. However, its strong product-specific effect in EU compensates for this, resulting in the highest Impact Score in this category. The $IS_{10,EU} = 2.41$ indicates that users highly value the ease of use of product 10, and this attribute significantly influences their acceptance. This suggests that Product 10 has a competitive advantage in Ease of Use and that this feature is critical to its market success.

In contrast, product 17 exhibits some of the lowest (negative) Impact Scores for PU and EU among all products ($IS_{17,PU} = -1.71$ and $IS_{17,EU} = -1.86$), indicating underperformance compared to other market products. Analysis of Figures 1a and 1b reveals product 17's positioning in the fourth quadrant for both PU and EU, suggesting that users perceive it as less useful and easy to use than competing products. This lower Perceived Usefulness and Ease of Use have less impact on user acceptance. However, this does not automatically imply market disadvantage. Figure 1c shows that Price Attractiveness, product 17 has the highest Impact Score, highlighting its competitive advantage in this feature.

Interpreting Impact Scores requires caution, as they depend on the acceptance model specified in H-TAM. Analysts must carefully select features for analysis, as these choices will guide conclusions about a product's strengths and weaknesses. While core technology acceptance variables like PU and EU are generally reliable for analyzing IT products, our model shows that focusing solely on these may overlook context-specific variables where other products may excel. Therefore, analyses using our framework should thoughtfully include all variables deemed relevant for the studied problem.

7. Discussion and further research direction

H-TAM is designed to bridge theoretical technology acceptance models and applied business and market research. The IS field has developed sophisticated theory around technology acceptance, yet translating this theoretical knowledge into practical business applications has received limited attention. In this paper, we establish the foundation for connecting IS theory with practical implementations. Through simulation, we demonstrate that paying attention to context differences and heterogeneity in model effect sizes can reveal previously omitted insights.

Our simulation assumes differences in effect sizes or the importance of certain predictors or attributes. This assumption is justified by both IS and business literature [6, 20, 27, 31]. Technology acceptance models have proven that predictors like Perceived Ease of Use are consistently significant. However, the strength of their effects almost always differs from context to context. Different user groups might value different attributes more, different products might underscore different features, and different organizations have different technology adoption rates. In all these cases acceptance predictors will have varying effect sizes. These differences can be informative, and this is the core value proposition of H-TAM: it investigates these differences, quantifies their magnitude, and through Impact Scores enables identification of advantages and disadvantages.

7.1. Applications and Generalizability

While we have focused on H-TAM's applicability in market research and product comparison, its potential extends far beyond this domain. With its flexible structure and focus on variability, H-TAM is useful in any applications where technology acceptance parameters differ across contexts. Among potential applications, we could consider cases where previous research has indicated variability in technology acceptance, such as:

- Healthcare technology adoption [10], where H-TAM could infer context effects arising from differences among healthcare providers or institutions.
- Educational technology [32, 34], which may involve assessing e-learning tool acceptance across schools, universities or distinct user groups, including students, teachers, and administrators.
- Financial services technology [29], where H-TAM can infer how varied customer segments or demographics engage with fintech solutions such as mobile banking or digital wallets.
- Organizational characteristics [8], where the specific characteristics of different organizations may significantly shape technology perception and adoption rates.

H-TAM's strength lies in its ability to infer and quantify context-effects wherever context-dependent phenomena exist. This principle of generalization extends to our Impact Score. For instance, in examining technology adoption across various organizations, with these organizations serving as the context units for context-effects, the Impact Score could reflect each organization's readiness or relative advantage/disadvantage in adopting the specified technology. The way researchers interpret this metric will pivot according to the specific research problem and questions they investigate.

7.2. Future Theoretical Development

Future research should develop a clear link between the results that H-TAM provides in the form of its Impact Scores and applied economics and business theory. One potential link that we foresee is the Importance Performance Analysis (IPA) that has been used in economics and management for product comparison and competitiveness analysis. Similar to acceptance models, IPA defines an outcome variable related to user satisfaction and product acceptance and uses predictors like product attributes to predict that outcome variable. IPA compares the strength (effect sizes) of certain predictors to determine which are the most important for product success. Similarly to H-TAM's Impact Scores, IPA also uses both the predictors' effect sizes and the predictors' means to judge product competitiveness. IPA seems like a prime candidate for integration with H-TAM. Further methods like SWOT analysis are also promising candidates.

Another further direction for H-TAM's expansion could be the inclusion of higher-order predictors from mixed-effect models (see Supplementary Materials for a brief review of higher-order predictors). These predictors aim to explain context-effects by incorporating features of the context units into the H-TAM equation. For example, when applying H-TAM to study context-effects across organizations, higher-order predictors could include variables like the industry sector or organization's workforce size. These predictors are used to explain the variability captured by the model's context-effects. We might discover that this variability arises because the private sector values ease of use more while government organizations give more weight to usefulness.

8. Conclusions

Technology acceptance theory has often been reduced to theoretical constructs, with insufficient emphasis on practical application. However, the value of a theory must be measured by its real-world applicability, and it is this aspect that technology acceptance models have often fallen short. We acknowledge technology acceptance theory's contributions, yet significant work remains in bridging theory to practice. The preoccupation with theoretical validation and model development within the scientific community has, at times, overshadowed the pursuit of practical utility.

We argue that one underlying reason for this neglect lies in the models' traditional conceptualization and the implicit fixed assumption, which have constrained the exploration of technology acceptance as a context-varying phenomenon. Our proposed Heterogeneous Technology Acceptance Model - intentionally described as such, rather than a theory - presents a new opportunity for the research community, as it invites a shift in focus towards the differences in technology acceptance across diverse and underexplored contexts. With the introduction of H-TAM, we anticipate a resurgence of interest in technology acceptance research, that will bring not only theoretical but also practical advancements.

Supplementary Materials.
The supplementary materials accompanying this article, including the code used for generating the data and detailed explanations, are available at the Open Science Framework. This repository provides additional resources that support the findings and methodologies described in the article. These materials can be accessed through the following link: https://osf.io/w92nt/

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