From Information Systems Theory to Market Intelligence: Heterogeneous Technology Acceptance Models as a Tool for Product Analysis

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Abstract

While Technology Acceptance Models (TAM) are widely used, their practical utility remains under scrutiny. This study investigates the usefulness of TAM for market intelligence by examining the heterogeneity of its predictors across different handheld gaming consoles. We collected user reviews for Nintendo, Steam Deck, Logitech, and Razer consoles from Amazon.com and annotated them using NLP-LLM to obtain scores for TAM variables. Separate TAM regressions were fitted for each console and compared using coefficient tests and ANOVA. Results supported the heterogeneity hypotheses, revealing significant differences in TAM coefficients across consoles. Steam Deck emerged as a market leader, while Nintendo lagged behind competitors. Logitech and Razer demonstrated comparative advantages in Perceived Usefulness over Ease of Use. We demonstrated that he model heterogeneity enables utilizing TAM for practical applications such as product comparison and design improvement prioritization. Companies can identify strengths, weaknesses, and user priorities for their products by jointly examining model coefficients and mean user sentiment scores.

Keywords: Technology Acceptance Model, Product Comparison, Comparative Analysis, Handheld Gaming Consoles

1. Introduction

The concept of technology acceptance has been a cornerstone in information system research for nearly four decades, igniting a plethora of studies dedicated to understanding it [1–4]. The idea of technology acceptance originates with the pioneering work of Fred Davis, who introduced the first Technology Acceptance Model in 1985 [5]. Davis's model aimed to understand an individual's willingness to adopt new technologies. Drawing from previous works by Ajzen Icek on social theory of reasoned action [6] and planned behavior [7], Davis identified two main determinants of technology adoption: Perceived Usefulness and Perceived Ease of Use [8]. Perceived Usefulness (PU) represents the user's expectation that a particular technology will improve one's job performance or everyday tasks. Conversely, Perceived Ease of Use (EU) represents the expectation that the technology will be simple and straightforward to use. These two variables are powerful determinants of user attitudes and behaviors towards technology but also demonstrate generalizability that allows them to be applied across diverse technology products.

In the years following Davis's initial model, the field witnessed explosive growth in technology acceptance research accompanied by numerous modifications and expansions of the original model [9–12]. Among these, Venkatesh's Unified Theory of Acceptance and Use of Technology (UTAUT) stands out as a particularly influential development [13], [3]. A simple search on Google Scholar with the keyword "UTAUT" yields over 80,300 entries, underscoring the theory's widespread adoption. Venkatesh expanded upon Davis's model by introducing four predictive variables: Performance Expectancy, Effort Expectancy (parallels of Perceived Usefulness and Ease of Use), Social Influence, and Facilitating Conditions. These variables have been validated by recent meta-analyses and literature reviews as the most reliable predictors of technology acceptance in a broad range of applications [2], [14].

While researchers have generally reached consensus regarding the best technology acceptance model, many scholars have questioned the practical utility of technology acceptance [15–18]. These scholars question what insights the understanding of technology acceptance determinants can provide, beyond the tautological conclusion that users adopt products perceived as useful and easy to use [15].

Over the past decade, scholars have attempted to provide practical applications of technology acceptance models by applying them to areas such as improving organizational readiness [19], product comparison [20, 21] and product design [17], [22, 23]. However, one barrier that limited the popularity of this practical application approach among researchers was the assumption that the technology acceptance predictors are homogeneous, meaning they have a consistent effect across all contexts. However, recent research has challenged this long-held assumption. As Salovaara et al. [17], [24] argued that treating the model's predictors as invariant (homogeneous) limits model's flexibility and applicability. The model then becomes unable to provide insights for improving products or tailoring implementations to specific contexts. Without heterogeneity in the predictors' effects across different contexts, the model offers little value beyond identifying general factors influencing technology acceptance. Salovaara et al. [17], [24] argued against the assumption of homogeneity. They asserted that for the model to be truly useful, it must incorporate heterogeneity in the effects of its predictors across different contexts. Recent meta-analytic results have provided empirical evidence supporting their argument, demonstrating that the model predictors are indeed heterogeneous and have varying effects depending on the context in which they are studied [14], [25].

Salovaara and Tamminen [17] contended that if the models' predictors are allowed to vary, the model could be utilized for practical purposes such as product design and product comparison. For example, if product A has a greater effect size of Ease of Use (EU) on user adoption than product B, then any improvements in design aimed at EU features should lead to greater adoption for product A compared to equivalent changes in product B's design. This does not mean that EU has no impact on product B. Instead, it simply indicates that the effect of EU is greater for product A than for product B. Research comparing the effect sizes of technology acceptance predictors has therefore been conducted in a variety of fields. For instance, Kwon et al. [20] estimated separate technology acceptance models for Facebook and Twitter use and compared the models' coefficients across the two platforms to conclude that Facebook has a comparative advantage in Ease of Use over Twitter.

2. Current Study

In this paper, we aim to explore the application of technology acceptance models to product comparison. Our focus is on an arbitrary but relevant technology product: gaming handheld consoles. For many years, the market for these consoles was largely monopolized by a single company, Nintendo, with its flagship product Nintendo Switch [26]. However, the emergence of new products like Valve's Steam Deck, Logitech G, and Razer Kishi has recently created competition. The addition of these new products presents an opportunity to examine user acceptance of handheld consoles assuming that the acceptance factors for their respective customer populations differ. We aim to test this assumption. If we find meaningful differences in model parameters and means, we could conclude that certain products have a competitive advantage over others in features such as usefulness or ease of use. The model coefficients would therefore reveal which acceptance factors are more important to the corresponding customer populations. The importance of these factors would therefore have significant implications for the future of product design and competition within this market.

2.1. Hypothesis

Our research requires four hypotheses. The first two hypotheses are typical for model validation and are a standard procedure in technology acceptance research. The latter two hypotheses are important for comparative product analysis and novel to the field of technology acceptance research.

1. **Model Fit Hypothesis**. Our first hypothesis states that technology acceptance predictors (like PU) will consistently demonstrate strong predictive power of user acceptance across different products. In mathematical terms, this hypothesis predicts that R-squared magnitude for models applied to various technology products (e.g., Nintendo, Steam Deck, Logitech, Razer) will be approximately the same, falling within the expected range of 0.6 to 0.7 [27].

$$R^2_{Nintendo} \approx R^2_{Steam\ Deck} \approx R^2_{Logitech} \approx R^2_{Razer} \approx 0.6 - 0.7 \qquad (1)$$

   A large R-squared means that the technology acceptance model variables will jointly be highly predictive of actual user acceptance, which is a desired and commonly found property of acceptance models.

2. **Parameter Significance Hypothesis**. Our next hypothesis posits that all parameters within our model that predict technology acceptance will be statistically significant across each product analyzed. This hypothesis can be stated that for any model parameter *i* (e.g., EU):

$$\beta_i \neq 0 \qquad (2)$$

   It is a common practice for researchers to test whether the parameters are significant when validating technology acceptance models.

3. **Heterogeneity Hypothesis**. This hypothesis is an extension of the previous one and a direct verification of Salovaara and Tamminen's [17] and Salovaara et al. [24] claim that the model parameters are heterogeneous. It can be formalized that at least one of the following inequalities is true:

$$\beta_{i\ Nintendo} \neq \beta_{i\ Steam\ Deck} \neq \beta_{i\ Logitech} \neq \beta_{i\ Razer} \qquad (3)$$

   If at least one parameter significantly differs, this indicates variation in the effect size of specific model parameters on user acceptance between products. Such variation enables the identification of comparative advantages through differences in these effect sizes.

4. **Mean Differences Hypothesis**. Our last hypothesis is complementary to the previous hypotheses and examines whether there are significant differences in the means of model variables across different products:

$$\bar{X}_{i\ Nintendo} \neq \bar{X}_{i\ Steam\ Deck} \neq \bar{X}_{i\ Logitech} \neq \bar{X}_{i\ Razer} \qquad (4)$$

   Mean Differences Hypothesis may appear similar to the Heterogeneity Hypothesis, however they are conceptually distinct. The Heterogeneity Hypothesis explores whether model predictors, such as Perceived Usefulness (PU), have different effects on users' acceptance of different products, questioning whether PU influences acceptance differently across various consoles. In contrast, the Mean Differences Hypothesis focuses on whether there are significant variations in how PU and other model features are perceived across different products. It aims to identify the raw differences in sentiment without directly correlating this sentiment to user acceptance or product choice. In our model we compare the mean (average) PU score for each product and the mean EU score for each product.

For example, if the average PU score for Product A is 4.2, and for Product B is 3.3, with this difference being statistically significant, it suggests that users perceive Product A as more useful on average compared to Product B. This relates to the Mean Differences Hypothesis. On the other hand, the Heterogeneity Hypothesis postulates that if the coefficient for PU in predicting acceptance is 0.7 for Product A and 0.4 for Product B, with a significant difference between these coefficients, it indicates that users of Product A are more sensitive to changes in Perceived Usefulness than users of Product B.

3. Method

3.1. Technology Acceptance Model

Several models exist for validating technology acceptance, with the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) being the most popular [1, 2]. UTAUT builds upon TAM by incorporating additional variables like Social Influence and Facilitating Conditions alongside Perceived Usefulness and Ease of Use (Performance Expectancy and Effort Expectancy in UTAUT terminology).

Although UTAUT has proven effective in certain contexts due to its broader range of predictors, recent meta-analyses indicate that the model's explanatory power still largely resides in the original TAM variables: Perceived Usefulness and Ease of Use [14], [28]. Furthermore, researchers studying acceptance of handheld consoles showed a preference for TAM and its core predictors over UTAUT [26]. Consequently, we adopted the TAM framework for our study, focusing on Perceived Usefulness and Ease of Use.

Another rationale for preferring a streamlined model is our objective to examine differences in model parameters across products. This approach necessitates multiple tests correction, which becomes increasingly complex with additional model parameters. By opting for a simpler model, we aim to maintain rigorous statistical control while achieving high explanatory power of TAM.

3.2. Data

In our study, we adopted a novel approach to collecting technology acceptance data. Traditional methods, such as questionnaires or expert interviews, have been widely used in the past. However, there has been a recent trend towards more ecologically valid data in the form of digital user feedback, such as customer reviews on e-commerce websites [29]. Following this approach, we scraped product reviews from the official Amazon.com pages of top handheld console manufacturers. A total of 1,170 reviews were collected, distributed as follows: Nintendo (480 reviews), Steam Deck (155 reviews), Logitech G (246 reviews), and Razer Kishi (289 reviews). We aimed for a balanced representation of all possible star ratings, which on Amazon span from 1 to 5 stars.

However, ecologically valid data, such as user reviews, lacks a numerical form that can be directly passed to statistical models. In our study, the data exists in the form of textual reviews that require annotation before numerical analysis can be performed. Fortunately, significant advancements in the field of Natural Language Processing (NLP) annotation systems have recently increased our capacity to analyze text. These systems process textual data and return numerical sentiment scores based on predefined dictionaries or models. The most promising NLP annotation systems are those based on Large Language Models (LLMs). Unlike traditional NLP algorithms that require dictionaries or sentiment mappings, LLM annotation systems leverage the vast amounts of data used to train the models, giving them broad applicability. These systems take user-generated text, such as product reviews, as an input and then output annotations reflecting user sentiment on desired variables such as PU and EU. Past research has investigated the effectiveness of LLM annotation systems, and demonstrated satisfying consistency and accuracy [30–32].

In our study, we adopted an LLM annotation system based on the GPT-4 API, which has been recently validated to accurately annotate sentiment related to TAM variables from textual data [32]. The annotation process was conducted solely on the review text, with the LLM system being oblivious to the numerical ratings given to products. This approach ensures that the sentiment analysis is based purely on the content of the reviews rather than being influenced by the star ratings. The reliability of the LLM annotation system applied to the TAM variables was validated in a previous study by Smolinski et al. [32]. Their study showed that the system produces scores highly similar to human expert annotations and consistent across different LLM annotation runs.

Not all reviews contained enough detail for our LLM annotation system to assign a sentiment score effectively. The exclusion of certain reviews was carried out automatically by the LLM annotation algorithm. This algorithm used a prompt adapted from Smolinski et al. [32] to determine whether the reviews contained sufficient detail for sentiment annotation. As a result, reviews lacking adequate information were excluded, leading to adjusted sample sizes: Nintendo (448 reviews), Logitech (240 reviews), Razer (282 reviews), and Steam Deck (135 reviews). Additional details about the exclusion prompt and annotation process are available in the Supplementary materials. A Python script for data scraping and the annotation task is provided in the Supplementary materials.

3.3. Regression models

Technology acceptance models are typically fitted using Structural Equation Modeling (SEM) or regression modeling. We have opted for the second approach, as SEM is preferred when there is a complex measurement model caused by questionnaire design and when the objective lies in complex parameter interactions or pathways. In contrast, we focus on a simple TAM with two parameters: Perceived Usefulness (PU) and Perceived Ease of Use (EU).

From the TAM regression model, the parameters of interest include R-squared and model parameter coefficients. R-squared explains the total predictive power of the TAM variables. The parameter coefficients represent the strength and direction of the relationship between the independent variables (here PU and EU ratings, obtained through Likert scale annotations from the LLM annotation system applied to user reviews) and the dependent variable (Acceptance – measured by the review's star rating). Variables with larger positive coefficients are considered more important determinants of technology acceptance.

3.4. Product comparison

Our hypotheses required comparative analysis, which we achieved by fitting regression models to each handheld console product separately and then running comparative tests on the parameters between the fitted models. Since the models for each product shared the same specification, we employed the method described by Ayala Cohen for comparing the effect sizes of parameters [33]. This procedure involved comparing the model's beta parameters using a special version of the t-test designed specifically for comparing regression coefficients. The result yielded a coefficient difference and a p-value indicating whether that difference was statistically significant. As our Heterogeneity Hypotheses required running multiple beta parameter tests, we needed to apply a correction for multiple testing. Popular corrections include Bonferroni, Sidak, Holm-Sidak, or FDR methods. We opted for the Holm-Sidak correction as it provided a good balance between maintaining the familywise error rate and preserving statistical power.

To test the Mean Differences Hypothesis in user perceptions of Technology Acceptance Model variables (e.g., PU scores) across different products, we employed a one-way analysis of variance (ANOVA). The ANOVA determined if the mean user sentiment on a particular variable differed significantly across the different handheld console groups. We then conducted post-hoc pairwise comparisons using the popular

Tukey method to identify which specific product pairs exhibited largest differences in user sentiment for each TAM variable. The Tukey method controlled the familywise error rate while maintaining reasonable statistical power.

4. Results

4.1. LLM annotation results

The LLM annotation system produced a data frame containing two columns with annotated Perceived Usefulness (PU) and Perceived Ease of Use (EU) scores on a Likert scale ranging from 1 to 5. These Likert scale annotations aim to mimic questionnaire behavior by annotating the sentiment expressed in the reviews related to each factor. An annotation of 1 indicates that the review clearly expresses negative sentiment toward the factor (e.g., PU), while an annotation of 5 represents a review that clearly expresses positive sentiment toward the factor. Mean sentiment annotations and their standard deviations for each handheld console are presented below in Table 1.

Table 1. Descriptive statistics for user star ratings of handheld consoles and mean Large Language Model annotations of Perceived Usefulness and Ease of Use sentiment.

	Rating		**Perceived Usefulness (PU)**		**Ease of Use (EU)**	
Product	Mean	SD	Mean	SD	Mean	SD
Nintendo	3.03	1.43	2.86	1.40	2.51	1.05
Steam Deck	3.98	1.56	3.68	1.39	3.24	1.15
Logitech	3.47	1.61	3.40	1.36	2.96	1.01
Razer	3.46	1.48	3.27	1.37	2.73	1.04

4.2. R squared (Model Fit Hypothesis)

In Table 2, we present the results from fitting TAM regression models for each product. The R-squared values support our Model Fit Hypothesis, which stated that technology acceptance predictors would consistently demonstrate strong predictive power of user acceptance across different products. All models reached the anticipated R-squared range of approximately 0.6-0.7. For instance, the R-squared value of 0.725 for the Razer console indicates that 72.5% of the variance in user ratings can be explained by the PU and EU scores. These values are typical for TAM and its variants, confirming that TAM is a valid framework for modeling user sentiment towards these products.

Table 2. Technology Acceptance Model regression results

	Perceived Usefulness (PU)		**Ease of Use (EU)**		R^2
Product	Coef. (SE)	p-value	Coef. (SE)	p-value	
Nintendo	0.499 (0.049)	< 0.001	0.458 (0.065)	< 0.001	0.606
Steam Deck	0.458 (0.098)	< 0.001	0.593 (0.117)	< 0.001	0.647
Logitech	0.719 (0.078)	< 0.001	0.372 (0.105)	< 0.001	0.648
Razer	0.795 (0.059)	< 0.001	0.197 (0.078)	0.012	0.725

4.3. Beta coefficients (Parameter Significance Hypothesis)

As expected, all model coefficients from Table 2 are significant, indicating that PU and EU are important determinants of user acceptance. This is not a surprising result, as pointed out by Barki and Benbasat's [15] critique of TAM: useful and easy-to-use products will always be used by users (and hence these variables will be significant). However, we can observe that the parameter coefficients have different effect sizes, and despite all being significant, some products have larger coefficients than others. These differences suggest underlying heterogeneity in TAM parameter estimates across products. They indicate that the strength of the relationships between the independent variables and user acceptance may vary among different handheld console offerings.

4.4. Effect size differences (Heterogeneity Hypothesis)

The analysis of model coefficient differences using the Cohen procedure (Table 3) suggests significant variability in coefficients across different technology products. This coefficient heterogeneity points to differing product-specific influences on user acceptance. For instance, in the case of Nintendo versus Razer, the comparison indicates statistically significant differences across all TAM coefficients. For Razer, the effect of PU on user acceptance is significantly larger, implying that PU has a stronger positive impact on user acceptance compared to Nintendo. However, Nintendo holds a significant advantage in the importance of EU which exerts a comparatively larger effect on user acceptance. This suggests that users place greater emphasis on the ease of use features when evaluating Nintendo products, as opposed to the Razer.

Guided by the recommendations of Salovaara et al. [24], we contend that once the differences between technology products are identified within technology acceptance models, this heterogeneity can be leveraged for product design and comparison. We discuss that in greater detail in the subsequent discussion section.

Table 3. Summary of effect size comparisons across products (Cohen procedure with Holm-Sidak correction)

Comparison	Variable	Coef. Difference	p-adj	Significant
Logitech vs Razer	PU	-0.075	0.995	No
	EU	0.174	0.150	No
Nintendo vs Logitech	PU	-0.219	0.018	Yes
	EU	0.086	0.897	No
Nintendo vs Razer	PU	-0.295	< 0.001	Yes
	EU	0.260	0.001	Yes
Nintendo vs Steam Deck	PU	0.041	1.000	No
	EU	-0.135	0.600	No
Steam Deck vs Logitech	PU	-0.261	0.049	Yes
	EU	0.221	0.142	No
Steam Deck vs Razer	PU	-0.336	0.003	Yes
	EU	0.395	< 0.001	Yes

Note. The magnitude represents the strength of the difference between groups, with larger absolute values indicating a more substantial difference. The sign (positive or negative) indicates the direction of the difference, where positive means the first product has a higher value compared to the second product, while a negative value means the opposite.

4.5. Mean differences (Mean Differences Hypothesis)

The results of one-way ANOVA showed a statistically significant difference in the average user star ratings ($F(3, 1101) = 15.82$, $p < 0.001$), average Perceived Usefulness ($F(3, 1101) = 16.31$, $p < 0.001$), and average Ease of Use ($F(3, 1101) = 20.57$, $p < 0.001$). Tables 4, 5, and 6 contain the post-hoc comparisons using the Tukey HSD test for user star ratings, PU annotations and EU annotations, respectively.

Table 4. Tukey's HSD for user star ratings

Comparison	Mean Difference	Lower	Upper	p-adj	Significant
Logitech vs. Nintendo	-0.444	-0.753	-0.135	<0.001	Yes
Logitech vs. Razer	-0.0098	-0.349	0.329	0.999	No
Logitech vs. Steam Deck	0.5069	0.091	0.922	0.009	Yes
Nintendo vs. Razer	0.4342	0.140	0.727	<0.001	Yes
Nintendo vs. Steam Deck	0.951	0.571	1.330	<0.001	Yes
Razer vs. Steam Deck	0.5168	0.112	0.921	0.005	Yes

Table 5. Tukey's HSD for Perceived Usefulness scores (LLM annotations)

Comparison	Mean Difference	Lower	Upper	p-adj	Significant
Logitech vs. Nintendo	-0.5384	-0.822	-0.254	<0.001	Yes
Logitech vs. Razer	-0.1305	-0.442	0.181	0.718	No
Logitech vs. Steam Deck	0.2815	-0.100	0.663	0.190	No
Nintendo vs. Razer	0.4079	0.137	0.677	<0.001	Yes
Nintendo vs. Steam Deck	0.8199	0.471	1.168	<0.001	Yes
Razer vs. Steam Deck	0.412	0.040	0.783	0.018	Yes

Table 6. Tukey's HSD for Ease of Use scores (LLM annotations)

Comparison	Mean Difference	Lower	Upper	p-adj	Significant
Logitech vs. Nintendo	-0.426	-0.663	-0.231	<0.001	Yes
Logitech vs. Razer	-0.207	-0.468	0.006	0.115	No
Logitech vs. Steam Deck	0.253	-0.012	0.569	0.112	No
Nintendo vs. Razer	0.219	0.010	0.421	0.033	Yes
Nintendo vs. Steam Deck	0.679	0.460	0.991	<0.001	Yes
Razer vs. Steam Deck	0.460	0.2271	0.7931	<0.001	Yes

The analysis of user ratings and LLM annotations for PU and EU among the various handheld consoles highlights significant disparities in user sentiment, particularly disadvantaging Nintendo. According to the results in Table 1, Nintendo registers the lowest means in both star ratings and annotations for PU and EU. This is reinforced by the post-hoc comparisons in Table 4-6, where Nintendo's ratings are significantly lower than those of its competitors, indicating a less favorable user perception.

In contrast, Steam Deck emerges as the favorite among users in all variables analyzed. It has significantly higher user ratings than all other products. According to Tables 5 and 6, Steam Deck outperforms its competitors in PU and EU annotations, with the exception of Logitech, where the differences are not statistically significant, indicating a similar level of user sentiment.

Logitech and Razer find themselves in a balanced position among competitors in this product category. An analysis of user sentiment reveals that they slightly outperform Nintendo in terms of user perception while trailing Steam Deck by a small margin.

5. Discussion

5.1. Comparative analysis

Our results strongly support the heterogeneity hypothesis, confirming that the TAM parameters, such as PU and EU, vary significantly between consoles. To make this observed heterogeneity meaningful and actionable, we need to interpret the results in a way that provides valuable insights for companies and market research. We postulate that there are two components of Technology Acceptance Models that are relevant for companies and product analysts: model coefficients and actual PU and EU scores.

The model coefficients represent consumers' sensitivities to the respective PU and EU of a product. These coefficients quantify the importance of PU and EU scores on consumers' overall evaluations or preferences for a product. The PU and EU scores themselves indicate users' sentiments towards specific product features. These scores can be derived from various sources such as user questionnaires, expert consultations, or, as in our case, annotated user reviews. On their own, PU and EU mean scores are useful for identifying products that are generally perceived more favorably by users regarding these characteristics. For instance, if a gaming console is noted for its high ease of use, it may be preferred by users who value simplicity in their gaming experience. However, these scores take on additional significance when analyzed jointly with model coefficients. One insightful scenario arises when a model displays high PU or EU coefficients but low PU and EU mean scores. Such a result would provide critical market intelligence for a company because it would indicate it can improve its acceptance amongst its users by focusing on such features. In contrast, companies with large PU or EU coefficients, but also high mean values, are not likely to be able to increase their acceptance higher by improving on PU or EU features as these are already excellent in the eyes of the consumer. Another possibility is when a product has low or even no significant coefficients. In this case, users do not heavily prioritize PU or EU for that product. Companies may choose to focus on other features that drive adoption instead.

5.2. Example of actionable insights for handheld gaming consoles

Based on the outlined logic, we have conducted a comparative analysis of four handheld gaming consoles, which offers actionable market intelligence for product development and marketing strategies. The findings from our mean difference analysis highlight that Nintendo's console struggles in terms of user acceptance, as evidenced by significantly lower mean star ratings and mean PU and EU sentiment scores compared to its competitors (see Table 1 and Table 4-6). We believe these averages indicate a possibility for improvement, particularly since these features hold significance for Nintendo's user base. The decision on which aspect to prioritize should be guided by the model's coefficients and a comparative analysis against competitors. According to our findings in Tables 2 and 3, while Nintendo's coefficients for PU and EU are relatively similar, it does show potential advantages in EU compared to other products. This suggests that focusing on ease of use might yield the greatest benefits, but emphasizing both features can help improve the console's overall acceptance.

We find Steam Deck in a contrasting situation, having significantly higher star ratings, PU and EU scores than most of its competitors. Both PU and EU coefficients exhibit comparable effect sizes, and a comparison of Steam Deck and Nintendo model coefficients does not reveal significant differences. Steam Deck emerges as a product with a favorable user perception, and our analysis positions it as a current benchmark for other handheld consoles concerning PU and EU features, providing valuable market intelligence for competitors.

The offerings from Razer and Logitech fall in between Nintendo and Steam Deck in terms of user acceptance, PU and EU scores. For instance, Razer may have an advantage over Nintendo in user acceptance and PU and EU features, but it lags significantly behind the market leader, Steam Deck, in terms of ratings and PU and EU scores. Similar to Nintendo, Razer's lower mean sentiment score and significant model coefficient suggest a room for improvement. However, in Razer's case, Table 2 and 3 clearly indicate that PU is the more important feature for its users, with a larger model coefficient than EU and significantly larger effect size than both Nintendo and Steam Deck. This market intelligence implies that Razer's handheld users are more sensitive to improvements in usefulness than ease of use and would value potentially improved PU features greater than improved EU features. A similar pattern is observed for Logitech, where its PU coefficient is significantly larger than its EU coefficient and larger than both Nintendo and Steam Deck. This indicates that both Razer and Logitech would benefit more from improving features that drive usefulness rather than ease of use.

5.3. Perceived Usefulness and Ease of Use product features

Perceived Usefulness (PU) and Ease of Use (EU) are terms integral to the Technology Acceptance Model. These constructs relate to the user's psychological experience of a technology product in these dimensions. Although these terms were originally defined by Davis in 1985, they may appear abstract for practitioners aiming to apply insights from acceptance studies. To make these abstract concepts more concrete and actionable for practitioners, we propose framing them in terms of Perceived Usefulness and Ease of Use product features, or PU and EU features for short. PU features of a technology product are those characteristics that directly contribute to its functionality and effectiveness in achieving specific tasks or goals, whereas EU features are those attributes of a technology product that make it straightforward and simple to use. For handheld gaming consoles, PU features might relate to processor speed, graphics quality, load times, cloud save functionality, or even the variety and exclusivity of games available on the console. EU features, in contrast, could include the simplicity and intuitiveness of navigation menus and system interfaces, portability, or ergonomics of the controller. While these features are inherently subjective, and their definition and perception may vary from user to user, they point toward a general improvement direction or potential weakness of the product. Understanding which PU or EU features are valued by product's users, and to what degree, can provide valuable market intelligence for companies.

6. Limitations and future studies

While this study provides novel insights into the application of Technology Acceptance Models for comparative product analysis, it is not without limitations. First, the data was sourced entirely from online user reviews on Amazon.com. While online reviews offer a wealth of accessible user sentiment data, they may not be fully representative of the entire user population for each product. Users who choose to leave reviews may systematically differ from those who do not.

Second, the study relied on a novel approach of using a Large Language Model (LLM) annotation system to extract numerical sentiment scores from the textual review data. While the reliability of this annotation system was validated in prior research, it is still an emerging technology and may be subject to biases or inconsistencies compared to traditional human annotation and questionnaire methods.

Finally, and perhaps most importantly, we captured user sentiment for a single iteration of each product (specifically the current newest model at the time of data collection). However, user perceptions and the relative importance of factors like usefulness and ease of use may evolve as products undergo updates and redesigns. The heterogeneity can occur not only between products but also within a single product as it undergoes updates and redesigns. For example, the early iterations of the Nintendo Switch faced limited competition in the handheld gaming market. During this period, the coefficient for Perceived Usefulness (PU) in the Technology Acceptance Model might have been relatively small, as users did not have many alternative devices to compare against. However, as competitors like the Steam Deck introduced more advanced features and hardware, the importance of PU for the Switch could have increased. Simultaneously, the Switch's technical limitations compared to newer entrants might have led to a decrease in its PU sentiment scores, as users' expectations for performance and functionality evolved.

Longitudinal studies that track changes in model coefficients and user sentiment across product iterations could provide valuable insights into these dynamics. Such research could help companies anticipate shifts in user priorities and adapt their product development and marketing strategies accordingly. Future studies could also explore the factors that drive changes in the importance of Technology Acceptance Model variables over time, such as evolving user expectations, technological advancements, or competitive landscape shifts.

We view these limitations as opportunities for future research. Future studies could explore how changes in user sentiment and model coefficients over time can determine product development, feature prioritization, and competitive positioning strategies.

Researchers could also investigate the factors that drive shifts in the importance of Technology Acceptance Model variables, such as evolving user expectations, technological advancements, or market disruptions. We hope that by leveraging the heterogeneity of Technology Acceptance Models and integrating them with market intelligence research, practitioners can gain a comprehensive understanding of user preferences and make data-driven decisions to optimize product design and marketing strategies in dynamic competitive landscapes.

7. Conclusions

We explored the application of the Technology Acceptance Model (TAM) for comparative product analysis across different handheld gaming consoles. While TAM has been widely adopted, we sought to address questions about its practical utility beyond confirming that users prefer useful and easy-to-use products. Recent research has suggested that TAM factors like Perceived Usefulness (PU) and Perceived Ease of Use (EU) must exhibit heterogeneity across products and contexts for the model to provide actionable insights.

We tested four hypotheses relating to model fit, parameter significance, heterogeneity of effects, and mean differences in PU and EU scores across Nintendo, Steam Deck, Logitech, and Razer handheld consoles. We found support for all hypotheses. We demonstrated that TAM has strong predictive validity across products, its PU and EU parameters are significant predictors of user acceptance, and crucially, the effect sizes of these parameters vary significantly between consoles (indicating heterogeneity). We also found substantial differences in the mean PU and EU sentiment scores for each product.

The observed heterogeneity in both model parameters and user sentiment enables us to leverage TAM for practical applications like product comparison and prioritizing design improvements. While it may seem we have merely shifted from stating “products that are useful and easy to use are used” to “improving products’ usefulness and ease of use will increase user adoption,” the coefficient heterogeneity and sentiment differences reveal these improvements are not uniform across products. If a product is already a top performer, further improvements may yield smaller acceptance gains as it is already perceived favorably. However, for underperforming products, we can identify strengths (e.g., larger PU coefficients) and weaknesses (lower PU sentiment) to guide strategic improvements. Producers aware of which factors matter most can prioritize improvements accordingly, rather than overemphasizing less impactful features.

Our findings showcase TAM’s utility in diagnosing relative product strengths, weaknesses, and consumer priorities within a market segment. We can identify areas for improving specific products by jointly examining model coefficients (reflecting consumer sensitivities to PU and EU) and mean PU and EU scores (reflecting general consumer sentiment toward existing features). Future research could extend our approach across broader technology domains and product categories. Incorporating additional TAM variables like social influence or product price may lead to additional insights. Triangulating multiple data sources beyond online reviews could also be beneficial. Overall, we believe that our study demonstrates TAM’s promising potential for transitioning from a purely academic model to supporting actionable business decisions in product development and marketing.

Supplementary Materials: Additional details including datasets and Python scripts are available in the supplementary materials at https://osf.io/v43km/.

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