

Factors Influencing AI-generated Storytelling to Engagement in Digital Market Opportunity for Sea Salt, Samut Songkhram, Thailand

Sumitra Nuanmeesri*, Lap Poomhiran, Shutchapol Chopvitayakun,
Preedawon Kadmateekarun

Department of Information Technology, Faculty of Science and Technology, Suan Sunandha Rajabhat University, Dusit, Bangkok, Thailand. *Corresponding Author's Email: sumitra.nu@ssru.ac.th

Abstract

This study investigates how AI-generated storytelling influences consumer perceptions, digital engagement, purchase intention and digital marketing opportunities for Thai sea salt as a cultural product in Samut Songkhram, Thailand. The study integrates Stimulus-Organism-Response (SOR) theory with Narrative Transportation Theory (NTT) to explain how narrative characteristics of AI-generated videos may shape consumer evaluations and behavioral responses. Data were collected from 125 Thai consumers aged 18 years and above who had experience using online platforms and purchasing products online. The proposed relationships were examined using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0. The results show that all five hypothesized relationships were statistically significant. Storytelling quality positively influenced perceived value ($\beta = 0.684$), while personalization positively influenced perceived benefit ($\beta = 0.612$). Perceived value was positively associated with digital engagement ($\beta = 0.548$) and perceived benefit was positively associated with purchase intention ($\beta = 0.592$). Digital engagement also showed a substantial association with digital marketing opportunity ($\beta = 0.724$; $f^2 = 1.102$). The model explained 61.8% of the variance in the study outcomes and demonstrated predictive relevance ($Q^2 = 0.425$). The findings suggest that AI-assisted cultural storytelling may support consumer evaluation and engagement when narrative content is culturally grounded and personalized. The study contributes a narrative-to-evaluation-to-behavior perspective that clarifies how NTT complements SOR in an AI-mediated marketing context. Practically, the findings guide the development of culturally grounded, emotionally engaging and personalized short-form video content for community-based products, an effective digital marketing strategy for promoting Thai sea salt products.

Keywords: AI-generated, Digital Marketing, PLS-SEM, Storytelling, Sea Salt.

Introduction

Sea salt has long been embedded in human economies, food systems and cultural practices, yet its contemporary value is increasingly challenged by technology, market competition and changing consumer perceptions (1, 2). In Samut Songkhram, Thailand, where sea-salt production remains closely connected with local knowledge and agricultural practices, traditional knowledge of weather conditions, salt-paddy management, water control, harvesting and storage is transmitted largely through families and oral traditions (3). When this knowledge is poorly communicated, sea salt may be perceived primarily as a commodity rather than as a product carrying cultural, ecological and production value. At the same time, salt has broader applications in industrial and food-related contexts. Sodium chloride is widely used as a raw material in

chemical industries, including the production of chlorine and sodium hydroxide (4), while research has examined mineral-water and thalassotherapy applications (5) and the role of sea salt in food and health products (6). These diverse dimensions indicate the need for communication approaches that can make local knowledge and product value understandable and meaningful to contemporary consumers. Digital storytelling provides one such approach by transforming complex cultural information into visual and audio experiences that can support awareness and engagement (7). Storytelling can also shape consumer brand experience (8), while recent work suggests that AI-assisted storytelling and visual metaphors can enhance experiences and engagement in digital environments (9). The growing importance of short-form video platforms further supports the

This is an Open Access article distributed under the terms of the Creative Commons Attribution CC BY license (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted reuse, distribution and reproduction in any medium, provided the original work is properly cited.

(Received 29th May 2026; Accepted 11th September 2026; Published 21st October 2026)

relevance of this approach in Thailand. Recent studies suggest that TikTok serves as an important digital marketing and social commerce platform among Thai consumers. Advertising characteristics, particularly interactivity and informativeness, along with customer brand engagement, have been associated with consumers' perceived value, trust and purchase intention. A study of 400 Thai TikTok users reported that TikTok-based marketing activities may contribute to consumer evaluations and behavioral responses (10). In addition, platform quality and relationship quality have been associated with purchase intention in TikTok social commerce, whereas social support was not statistically significant in the study. Based on responses from 825 Thai TikTok users, the findings suggest that TikTok provides a relevant digital setting for examining how marketing content and platform-related experiences may relate to consumer evaluations and purchase-related responses in Thailand (11). Therefore, TikTok may be an appropriate digital channel for communicating the characteristics, local knowledge and cultural narratives of community-based products to contemporary consumers. Within this environment, artificial intelligence has increasingly become a creative resource for combining data, narrative structures and multimedia production, thereby changing how cultural and marketing messages can be developed (12). In cultural-product contexts, AI can support the reinterpretation of local narratives into accessible multimedia content and potentially reduce production barriers for community enterprises (13, 14). Reviews and empirical studies further indicate that AI is expanding the creative industries and technology-enhanced storytelling, including applications involving digital humans and generative-AI co-creation (15-17). Generative AI may therefore help community producers document, interpret and communicate intangible cultural heritage through digital content, supporting safeguarding and continuity while enabling participation in digital creative activities and engagement with digital markets (18, 19).

However, existing research also reveals an important conceptual limitation. Studies of digital storytelling have established links with consumer experience, engagement, authenticity and

behavioral intentions (20, 21), but less attention has been given to how AI-generated cultural narratives are psychologically processed in ways that may shape consumer evaluations and subsequent behavioral responses. Research has not sufficiently clarified how narrative characteristics, such as story credibility, attention, emotional engagement and mental imagery, connect the external storytelling stimulus with perceived value, perceived benefit, digital engagement and purchase intention within a single explanatory sequence. This gap is important for community-based cultural products because their market value may depend not only on functional attributes but also on the meanings, experiences and local knowledge communicated through the narrative.

To address this gap, the present study integrates Stimulus-Organism-Response (SOR) theory with Narrative Transportation Theory (NTT). SOR conceptualizes external stimuli as influencing internal organismic states that subsequently shape behavioral responses (22) and its application has been extended to technology-adoption and digital-experience contexts (23). NTT complements this perspective by explaining how individuals can become psychologically involved in narratives through attention, imagery and affect, increasing receptivity to narrative messages (24, 25). Recent research further demonstrates that NTT and message congruity can influence subsequent behavioral responses (26). In the present study, NTT is therefore treated as a theoretical psychological processing mechanism rather than as a separately estimated statistical mediator. The integration proposes a narrative-to-evaluation-to-behavior mechanism: AI-generated storytelling characteristics and personalization constitute stimuli; narrative processing provides the psychological basis for consumers' internal evaluations; perceived value and perceived benefit represent organismic evaluations; and digital engagement and purchase intention represent behavioral responses. Digital marketing opportunity is positioned as a downstream construct representing perceived market potential associated with these responses.

Accordingly, this study aims to examine how AI-generated storytelling characteristics and personalization relate to consumer evaluations and behavioral responses toward Thai sea salt as a

community-based cultural product. Specifically, it evaluates the relationships between storytelling quality and perceived value, personalization and perceived benefit, perceived value and digital engagement, perceived benefit and purchase intention and digital engagement and digital marketing opportunity using Partial Least Squares Structural Equation Modeling (PLS-SEM). The theoretical contribution lies in specifying a narrative-to-evaluation-to-behavior mechanism that clarifies how NTT complements SOR in explaining consumer responses to AI-generated storytelling. By applying this integrated perspective to a culturally embedded local product, the study provides a theoretically grounded account of how AI-assisted storytelling may support culturally grounded digital marketing. The study does not, however, directly measure environmental, social, or economic sustainability outcomes. Therefore, any implications for sustainable marketing are considered conceptual rather than empirically demonstrated.

The remainder of this paper is organized as follows. Section 2 describes the methodology, including the research design, participants, measurement instruments, data collection procedure and data analysis using PLS-SEM. Section 3 presents the empirical results, including the measurement and structural model assessment. Section 4 discusses the findings in relation to previous research and the theoretical and practical implications of the study. Finally, Section 5 concludes the paper by summarizing the main findings, contributions, limitations and directions for future research.

Methodology

Participant and Sample Size

The target population comprised Thai consumers aged 18 years and above who had previously used the internet and purchased goods online. The selection of this population was motivated by the widespread use of social media and TikTok in Thailand and the growing role of TikTok Shop in social commerce (10, 11). This context provides a relevant setting for examining consumer responses to AI-generated storytelling in a digital marketing environment. The study was conducted using an online questionnaire that was available to eligible participants for 90-days. Ethical approval

was obtained before data collection. Before completing the questionnaire, participants were provided with information about the study objectives, voluntary participation, confidentiality and their opportunity to seek clarification. A total of 125 valid responses were retained for PLS-SEM analysis (27-29). Demographic information was collected solely to describe the sample and contextualize the findings. It was not used to infer differences between demographic groups or to conduct multi-group analysis.

Hypotheses and Measurement

Indicators

This work proposed the SOR-NTT conceptual framework (Stimulus-Organism-Response with Narrative Transportation Theory), which integrates the SOR theory with NTT to explain how AI-generated storytelling influences users' perceptions, behavioral engagement and market opportunity in the digital environment and to examine the influence of storytelling quality on digital behavioral outcomes and market opportunity. The framework consists of four dimensions: Stimulus (S), Organism (O), Response (R) and Outcome (OC). The model operationalizes Storytelling Quality (STQ) and Personalization (PER) as stimuli, Perceived Value (PV) and Perceived Benefit (PB) as organismic evaluations, Digital Engagement (DE) and Purchase Intention (PI) as responses and Market Opportunity (MO) as an extended market-level outcome. Based on this theoretical framework, five research hypotheses were formulated for empirical testing as follows.

H1: STQ in AI-generated videos has a positive effect on PV.

H2: PER of AI-generated video content positively influences PB.

H3: PV has a positive effect on DE.

H4: PB has a positive effect on PI.

H5: DE has a positive effect on digital MO.

The five hypotheses test the structural relationships within this mechanism:

H1 examines STQ → PV; H2 examines PER → PB; H3 examines PV → DE; H4 examines PB → PI; and H5 examines DE → MO.

These relationships were specified before analysis and evaluated using PLS-SEM. No demographic group comparisons were performed. Therefore, measurement invariance was not required for the analyses reported here. Future research that compares demographic or consumer segments

should establish measurement invariance before interpreting group-specific differences.

To validate the framework, the study employed PLS-SEM to assess the measurement and structural models. Reliability and validity were examined using factor loadings, Composite Reliability (CR), Average Variance Extracted (AVE) and the Heterotrait–Monotrait ratio (HTMT). Structural assessment included Variance Inflation Factor (VIF), path coefficients (β), t-values, p-

values, effect sizes (f^2), coefficient of determination (R^2), predictive relevance (Q^2) and model-fit indicators including Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), Unweighted Least Squares Discrepancy (d_ULS) and Geodesic Discrepancy (d_G). The analysis was conducted using SmartPLS 4.0. Statistical significance was interpreted together with effect sizes, R^2 and Q^2 rather than by p-values alone, as shown in Figure 1.

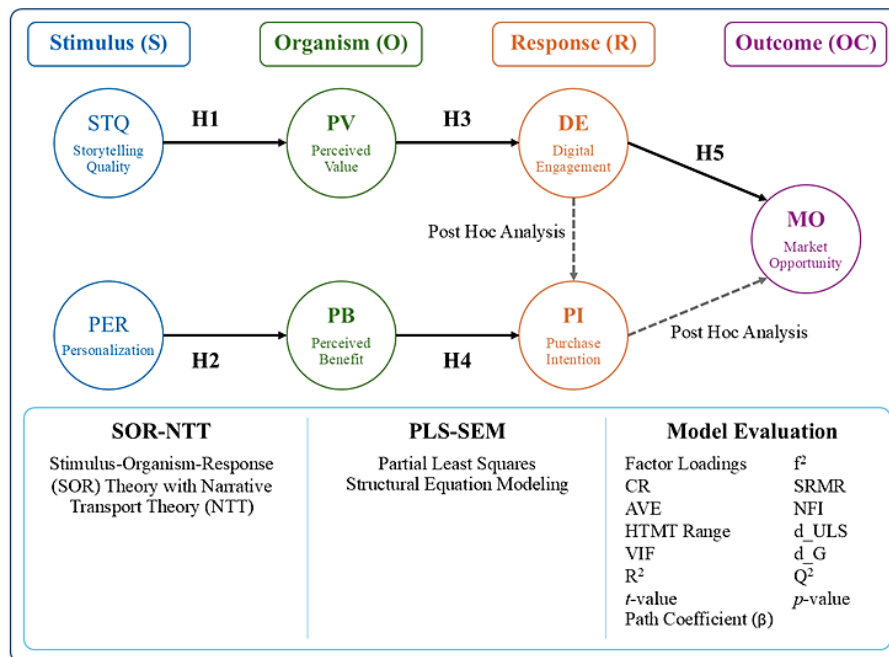


Figure 1: SOR-NTT Conceptual Framework

This research integrates clearly defined operational guidelines for each component within the SOR-NTT framework. This enables an explanation of the mechanisms underlying consumer perception and behavior in response to AI-generated narrative videos for sea salt products, as shown in Tables 1 and 2.

Hypothesis 1 (H1) proposes that STQ serves as a stimulus that influences PV. The STQ indicators capture essential dimensions of NTT, including Narrative Processing (NP), Affect (A) and Empathy and Emotion (EE), such as storyline clarity, creativity, attractiveness and emotional engagement. In this context, STQ represents S, which shapes consumers' perceptions of product value in terms of quality, cost-effectiveness and differentiation. These perceptions are associated with EE, NP and Mental Imagery (MI), in which PV serves as O. Next, Hypothesis 2 (H2) examines the influence of PER as a stimulus on PB. PER indicators reflect personalized content character-

istics related to A, MI and EE, while PB indicators emphasize awareness of product usefulness, usability and consumer confidence. Within this relationship, PER serves as S. In contrast, PB represents the O. Meanwhile, Hypothesis 3 (H3) suggests that PV, as an organism variable, positively affects DE, which functions as R. DE indicators include digital interaction behaviors such as liking, sharing, commenting, following channels and participating in online activities. These engagement behaviors are strongly associated with EE and A. Then, Hypothesis 4 (H4) proposes that PB, operating at the organism level, positively influences PI at the response level. PI indicators include consumers' willingness to purchase, future interest and intention to try the product, all of which are closely linked to EE. Accordingly, PI functions as R. Finally, Hypothesis 5 (H5) explains that DE positively contributes to MO, representing extended outcomes at the digital market level. MO indicators include enhanced

visibility, broader market reach and the creation of new business opportunities. In this process, NTT dimensions related to A and MI play a significant

role in strengthening digital marketing outcomes, with MO functioning as R.

Table 1: Hypotheses and Measurement Indicators

Hypotheses	Code	Measurement Indicators	NTT	SOR Model
H1: STQ in AI-generated videos has a positive effect on PV	STQ1	AI-generated videos feature clear and easy-to-understand storylines.	NP	S
	STQ2	AI-generated videos offer engaging and attractive content.	A	
	STQ3	AI-generated videos can reflect local culture and wisdom.	NP	
	STQ4	AI-generated videos are cutting-edge and creative.	A	
	STQ5	AI-generated videos can evoke emotions.	EE	
	STQ6	AI-generated videos have coherent storylines and an easily understandable structure.	NP	
H2: PER of AI-generated video content positively influences PB.	PV1	Sea salt is more valuable in consumers' eyes.	EE	O
	PV2	Consumers perceive sea salt as high-quality and clean.	NP	
	PV3	Sea salt offers good value for money to consumers.	NP	
	PV4	Sea salt has unique characteristics unlike industrial or rock salt.	MI	
	PV5	Sea salt is distinct from typical alternative products.	MI	
	PER1	The video content matches my interests.	A	S
	PER2	The information provided matches my needs.	A	
	PER3	The video helped me better understand the uses of sea salt.	MI	
	PER4	The content focuses on health-related benefits.	EE	
	PER5	The video presents practical demonstrations of its use.	MI	
	PER6	The content is relevant to my personal context.	EE	O
	PB1	The AI-generated video shows that sea salt has health benefits beyond its saltiness.	NP	
	PB2	The AI-generated video shows the benefits of sea salt in daily life.	MI	
	PB3	The AI-generated video encourages consideration of trying sea salt.	EE	
	PB4	The AI-generated video shows that sea salt can meet a range of uses.	MI	
H3: PV has a positive effect on DE.	DE1	AI-generated video increases the likelihood of sharing the video.	EE	R
	DE2	AI-generated videos increase the likelihood that viewers will like them.	EE	
	DE3	AI-generated video increases the likelihood of commenting and recommending on the content.	EE	
	DE4	AI-generated video increases the likelihood of following the brand's digital channel.	A	
	DE5	AI-generated videos increase the likelihood of participation in both in-person and online events.	EE	
H4: PB has a positive effect on PI.	PI1	AI-generated video increases the likelihood of purchase intent for this sea salt.	EE	R
	PI2	AI-generated video increases the likelihood of considering purchasing sea salt in the future.	EE	
	PI3	AI-generated video increases the likelihood of being willing to try sea salt.	EE	
H5: DE has a positive effect on digital MO.	MO1	AI-powered videos help increase the visibility of sea salt in the digital age.	A	R → Outcome Extension: Market-level outcome
	MO2	AI-powered videos help increase access to digital markets.	A	
	MO3	AI-powered videos help create business opportunities for sea salt in the digital world.	MI	

Note: AI = Artificial Intelligence, H = Hypothesis, STQ = Storytelling Quality, PV = Perceived Value, PER = Personalization, PB = Perceived Benefit, DE = Digital Engagement, PI = Purchase Intention, MO = Market Opportunity, NTT = Narrative Transportation Theory, NP = Narrative Processing, A = Affect, EE = Empathy and Emotion, MI = Mental Imagery, SOR = Stimulus-Organism-Response, S = Stimulus, O = Organism, R = Response.

Table 2: Construct Specification and Measurement-source Verification Matrix

Indicator set	Construct / Theoretical Basis	Specification	References
STQ1-STQ6	Storytelling Quality; narrative processing, affect, emotional engagement	Reflective	(7, 8, 16, 24-26)
PER1-PER6	Personalization; relevance, needs, context, imagery and engagement	Reflective	(9, 13, 14, 16, 17)
PB1-PB6	Perceived Benefit; usefulness and benefit evaluation	Reflective	(13, 14, 22, 23, 30)
DE1-DE5	Digital Engagement; behavioral response	Reflective	(25, 26, 29, 30)
PI1-PI3	Purchase Intention; behavioral intention	Reflective	(20, 21, 29)
MO1-MO3	Market Opportunity; extended market-level perception	Reflective	(13, 14, 18, 31)
PV1-PV5	Perceived Value; consumer value evaluation	Reflective	(13, 32, 33, 34, 35)

Note: STQ = Storytelling Quality, PV = Perceived Value, PER = Personalization, PB = Perceived Benefit, DE = Digital Engagement, PI = Purchase Intention, MO = Market Opportunity.

Data Collection

Data were collected through an online questionnaire. However, the research site that collected data on sea salt farming methods was located at approximately 13.416851° N, 100.047365° E (Bang Kaeo Sub-District, Mueang District, Samut Songkhram Province, Thailand). The study was open to eligible participants for 90-days, from November 2025 through February 2026 and 125 valid responses were retained. Demographic and contextual variables included gender, age, education level, online shopping experience through TikTok and TikTok platform experience. These variables were used to describe the sample and contextualize the findings rather than to compare demographic groups.

Instrument Construction and Validation

The questionnaire used a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). A panel of five experts (three in information systems and two in digital marketing) evaluated item relevance, clarity and cultural appropriateness for the Thai context. The Content Validity Index (CVI) exceeded 0.70 for all items, indicating an acceptable level of content validity (30). Internal consistency and convergent validity were assessed using Cronbach's alpha, CR and AVE. We specified the constructs as reflective because the observed indicators were treated as manifestations of their corresponding latent constructs and evaluated using indicator loadings, CR and AVE.

Measurement Model and Data Analysis

This study employed an indicator design based on an expert-evaluated framework, comprising six main variables (STQ, PV, PER, PB, DE and PI; 34

indicators in total) and MO as the outcome variable. Each variable was defined using multiple indicators adapted from validated scales and participants rated each indicator on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Data were analyzed using SmartPLS 4.0, which is efficient for examining complex models. PLS-SEM was chosen for this research because it suits complex multivariate models and relatively moderate sample sizes (31). Furthermore, PLS-SEM is particularly useful for predictive-oriented studies that do not assume strict normality, making it highly appropriate.

The reliability of the measurement model was assessed using several criteria. CR was used to assess internal consistency, with values above 0.70 considered acceptable and values below 0.95 used to avoid excessive redundancy (28). These values were selected as good indicators. Convergent validity was assessed using AVE, with values above 0.50 indicating that the construct explains at least half of the variance in its indicators (32). Discriminant validity was assessed using HTMT, with values below 0.85 interpreted as evidence that constructs are empirically distinguishable (33). These criteria were applied consistently across the seven reflective constructs.

Structural-model assessment considered collinearity, path coefficients, statistical significance, effect sizes, coefficient of determination, predictive relevance and model-fit indicators. Collinearity among predictor constructs was assessed using the VIF. The VIF values below 3.30 were interpreted as indicating that collinearity was unlikely to threaten the estimation of the structural model (36). Discriminant validity was assessed separately using the HTMT criterion and

should not be interpreted as a test of multicollinearity. The path coefficient (β) was used to determine the direction and magnitude of effects (36). It was always considered alongside t- and p-values. The t-value was used to test statistical significance, with a threshold value of at least 1.96 for a two-tailed test at the 5% significance level. The p-value was used to assess statistical significance, with $p < 0.05$ indicating evidence against the null hypothesis (28). The effect size (f^2) was used to assess the substantive contribution of each exogenous construct to an endogenous construct, with values of 0.02, 0.15 and 0.35 generally interpreted as small, medium and large effects, respectively (36). The coefficient of determination (R^2) value was used to assess the coefficient of determination of the endogenous constructs. Although its interpretation should consider the research context and model complexity, values of 0.25, 0.50 and 0.75 may be regarded as weak, moderate and substantial, respectively (34). Furthermore, predictive relevance was assessed using the predictive relevance (Q^2) value, for which values greater than zero indicate predictive relevance for a given endogenous construct (34). For behavioral intention, an R^2 value of 0.25 or higher was additionally used as a practical benchmark for evaluating explained variance (20). Moreover, model fit was examined using SRMR and NFI. The SRMR was assessed, with a threshold of 0.08 or lower to support model quality. The NFI and Squared Euclidean Distance (d_{ULS}) were also tested, along with the p-value for the confidence interval, to determine the model's fit to the empirical data (35, 37). This approach avoids interpreting statistical significance alone as evidence of practical importance.

Results

Results of the Sample Descriptive Analysis

The sample comprised 125 participants. The demographic profile is presented in Table 3. Data analysis revealed that most of the sample were male (70 people, 56%), followed by female (50 people, 40%) and 5 people of other genders (4%). This reflects that most respondents are male, suggesting a high level of familiarity with digital platforms and social media. Regarding age, the majority were aged 18–30 years (96 people, 76.8%), followed by those aged 31–60 years (20 people, 16%) and those aged over 60 years (9 people, 7.2%). This shows that most respondents are teenagers and young adults. This group uses TikTok and other digital media consistently and is more likely than other age groups to embrace new media formats, such as AI-generated storytelling. Regarding educational attainment, 93 individuals (74.4%) in the sample held a bachelor's degree. This was followed by those with degrees below a bachelor's degree (28 individuals, 22.4%) and those with degrees above a bachelor's degree (4 individuals, 3.2%). This suggests that most respondents have an educational background that enables them to access and understand digital content effectively, which in turn affects their awareness of information and their participation in online media. Regarding the online shopping experience via TikTok, most respondents (72 people, 57.6%) reported a high level of experience, followed by a moderate level (50 people, 40%) and a low level (3 people, 2.4%). This indicates that most respondents are familiar with purchasing goods through the TikTok platform, which may contribute to their ability to perceive and evaluate digital marketing content effectively.

Table 3: Sample Characteristics

Item	Number of samplings	Percentage (%)
Gender		
Female	50	40
Male	70	56
Other	5	4
Age		
18-30	96	76.8
31-60	20	16
More 60	9	7.2
Education		
Below a bachelor's degree	28	22.4
Bachelor's degree	93	74.4

Higher bachelor's degree	4	3.2
Shopping online on the TikTok platform experience		
High	72	57.6
Moderate	50	40
Low	3	2.4
TikTok platform experience		
High	98	78.4
Moderate	24	19.2
Low	3	2.4

Furthermore, regarding the overall TikTok user experience, most respondents (98 people, 78.4%) reported a high level of experience, followed by a moderate level (24 people, 19.2%) and a low level (3 people, 2.4%). This suggests that most respondents are regular TikTok users and are familiar with the platform's content format, short videos and digital communication. These characteristics indicate that the respondents were familiar with short-form digital content and online shopping; however, they should be interpreted as sample characteristics rather than evidence of demographic differences or causal effects.

Results of the Heatmap for Correlation Analysis

This study used a heatmap to illustrate correlations among all questionnaire variables, with color coding indicating the strength of each relationship. This can be interpreted as follows: light yellow-green indicates a high level of positive correlation, green-blue indicates a moderate level of positive correlation and dark blue-purple indicates a negative or low level of correlation. The analysis revealed that most variables exhibited low-to-moderate positive correlations, indicating that the model's variables tended to move in the same direction and that the model adequately described the research's conceptual structure. The STQ, PER and PB variables showed relatively high within-group correlations, demonstrating internal consistency and reflecting respondents' similar perceptions of these components. Additionally, PI

and MO showed positive correlations with several variables in the model, particularly with the PV and PB groups. This may reflect that increased consumer perception of the value or benefits of AI-generated storytelling content leads to higher digital marketing intent and opportunities. Overall, this heatmap confirms that the data structure is consistent with the theoretical framework and that no strong negative correlations are evident among most variables, as shown in Figure 2.

The heatmap analysis reveals that the STQ indicators (STQ1–STQ6) exhibit low-to-moderate positive correlations with one another. This reflects the interconnectedness of AI-generated storytelling video quality across various NTT dimensions, particularly STQ2 and STQ3, which show a relatively high correlation compared to other variables within the same group. This indicates that consumers who perceive content quality in one aspect tend to perceive other aspects positively as well. Theoretically, this reflects NTT's concept that high-quality storytelling elements work together to create MI and EE. Furthermore, an analysis of the correlation between STQ and PV was found. The heatmap shows that several STQs have positive correlations with PV1–PV5, especially STQ2 with PV3 and STQ3 with PV3, which are shown in brighter colors than the other values. This result indicates that when consumers perceive an AI-generated storytelling video as high quality, it positively affects their evaluation of the product's PV and the content.

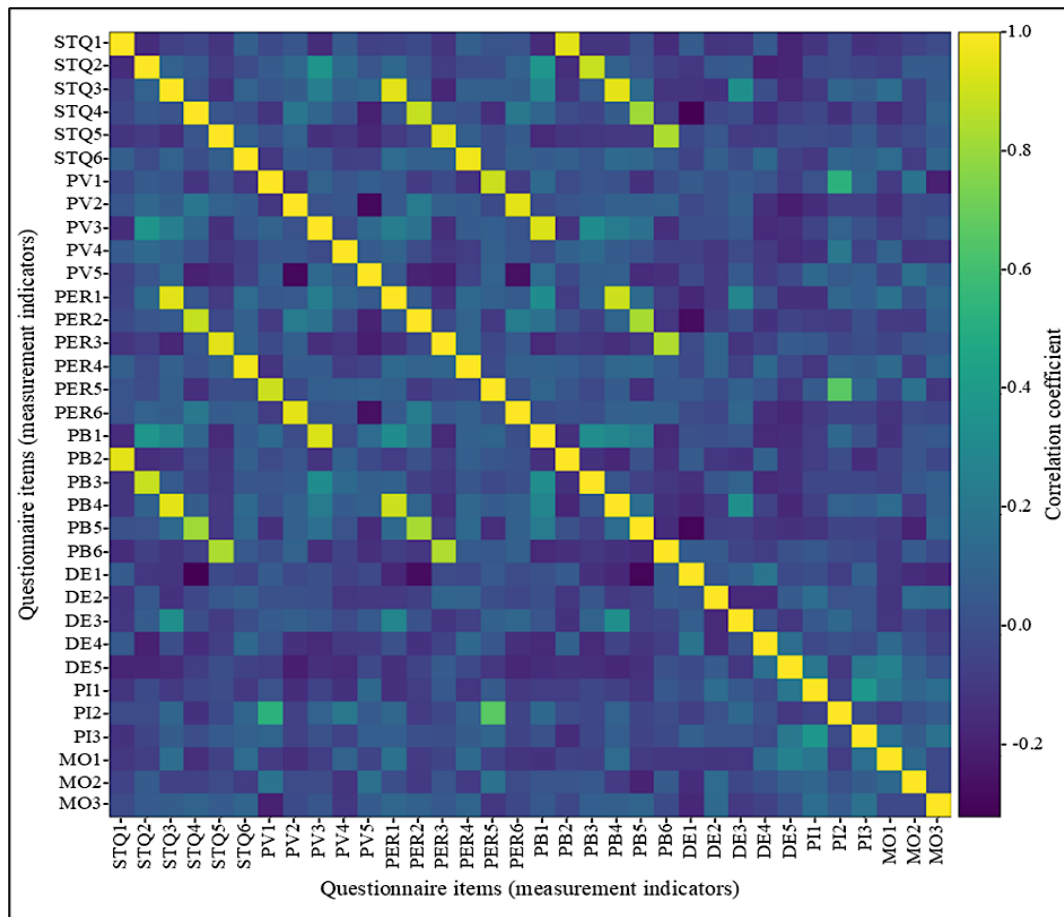


Figure 2: Results of the Heatmap for Correlation Analysis

Note: STQ = Storytelling Quality, PV = Perceived Value, PER = Personalization, PB = Perceived Benefit, DE = Digital Engagement, PI = Purchase Intention, MO = Market Opportunity.

Subsequently, the analysis of the PER indicator variables (PER1–PER6) revealed moderate positive correlations among the indicators. PER2, PER3 and PER4 exhibited a distinct green-yellow clustering pattern in the heatmap, indicating that AI-driven personalization significantly influences user perceptions across several dimensions, including content relevance, customization and the overall user-fit experience. Moreover, PER demonstrated positive associations with PB, particularly between PER3 and PB4 and between PER4 and PB5, suggesting that personalized AI content enhances consumers' perceptions of product benefits and usability. Moreover, the heatmap analysis of the PV and PB indicator groups revealed relatively strong positive correlations within and across constructs. This finding suggests that consumers who perceive greater value in AI-generated content are also more likely to perceive higher levels of product benefits. In addition, the DE indicator group (DE1–DE5) showed consistently positive correlations

with both PV and PB. These results indicate that higher perceived value and benefit from AI storytelling are associated with stronger digital engagement behaviors, such as clicking, sharing, participating, interacting with content and spending more time on the platform.

Furthermore, the analysis of the PI indicator group shows that PI1–PI3 have a moderate positive correlation with PB and DE. This indicates that purchase intention is based not solely on perception but also on the level of engagement consumers have with the content. Furthermore, the analysis of the MO indicator group, specifically the variables MO1–MO3, showed a clear positive correlation with DE and PI. This suggests that digital engagement and purchase intention are key variables that impact digital marketing opportunities. Across the entire heatmap, the variables showed a continuous positive correlation, supporting the SOR-NTT concept. Moreover, the heatmap did not reveal any strong negative correlations among the main variables,

reflecting high internal coherence in the model and a data structure that aligns well with the theoretical framework. This is a positive sign and provides a basis for further PLS-SEM data analysis.

Results of Measurement Model

Assessment

The measurement model was evaluated for factor loadings, CR, AVE and discriminant validity, evaluated using HTMT, as presented in Table 4. From the analysis of the PLS-SEM model to examine the validity and accuracy of the indicators (Measurement Model) based on the SOR-NTT frameworks, using a bootstrapping process of 10,000 iterations, the parameters of the stimulus were found and content validity and factor loadings were assessed by considering the factor loadings of each indicator item. All 34 indicators had factor loadings between 0.755 and 0.905, exceeding the statistically acceptable criterion of 0.708 (35). This result demonstrates that each indicator significantly explains the variance of the latent variable, particularly the PI indicator, which had the highest weight. This reflects the instrument's ability to capture emotional engagement with purchase intention clearly. CR is a criterion for assessing the internal consistency of a set of indicators measuring the same construct. The composite reliability values for all latent variables (STQ, PER, PV, PB, DE, PI, MO) ranged from 0.895 to 0.928, exceeding the recommended threshold of 0.700. Results exceeding 0.800 across all variable levels indicate excellent reliability, confirming that the research instrument is consistent in its measurements, whether

measuring PV or PB. The data obtained has low error and is sufficiently reliable. Results of the AVE Validation. It measures the proportion of variance in the indicators explained by their associated latent variables. All latent variables have AVE values in the range of 0.589 to 0.811, which meets the minimum standard criterion of 0.500. An AVE value at this level indicates that the latent variables can, on average, account for more than 65% of the variance in the indicators. In particular, the PI dimension, with the highest AVE (0.811), demonstrates convergent validity. The results of the HTMT range assessment, using the HTMT criterion, are widely accepted as the most accurate method for differentiating between variables. The analysis revealed that the HTMT values for all latent pairs in the model ranged from 0.412 to 0.814, which remain below the stringent criterion of 0.850. It can be concluded that each variable in the model is completely independent (Discriminant Validity) and shows no statistical overlap, even if they belong to the same structural group under the SOR framework. For example, the independent variables in the Stimulus group between STQ and PER were clearly distinguishable by the respondents. The model testing results show that all indicators identified according to the SOR (Stimulus, Organism, Response) and NTT (e.g., NP, A, EE, MI) structured clustering principles exhibit good statistical quality in indicator weights, internal consistency reliability and convergence and discriminant validity. This results in a robust model suitable for causal relationship analysis, enabling statistical testing of the five hypotheses in the next step.

Table 4: Results of the Measurement Model Evaluation

SOR Construct	NTT Construct	Indicators	Factor Loadings	CR	AVE	HTMT Range
S: Storytelling Quality	NP	STQ1	0.812	0.916	0.647	0.412 - 0.765
	A	STQ2	0.784			
	NP	STQ3	0.815			
	A	STQ4	0.792			
	EE	STQ5	0.821			
	NP	STQ6	0.810			
S: Personalization	EE	PER1	0.755	0.895	0.589	0.488 - 0.732
	NP	PER2	0.784			
	NP	PER3	0.762			
	MI	PER4	0.771			
	MI	PER5	0.758			
	A	PER6	0.774			
O: Perceived Value	A	PV1	0.831	0.902	0.650	0.488 - 0.765
	MI	PV2	0.798			
	EE	PV3	0.785			

	MI	PV4	0.812			
	EE	PV5	0.804			
O: Perceived Benefit	NP	PB1	0.791	0.909	0.625	0.512 - 0.745
	MI	PB2	0.772			
	EE	PB3	0.768			
	MI	PB4	0.815			
	EE	PB5	0.794			
	MI	PB6	0.806			
R: Digital Engagement	EE	DE1	0.842	0.915	0.684	0.521 - 0.814
	EE	DE2	0.815			
	EE	DE3	0.804			
	A	DE4	0.852			
	EE	DE5	0.821			
R: Purchase Intention	EE	PI1	0.892	0.928	0.811	0.442 - 0.745
	EE	PI2	0.905			
	EE	PI3	0.904			
Outcome (Extension):	A	MO1	0.858	0.901	0.752	0.485 - 0.814
Market Opportunity	A	MO2	0.871			
	MI	MO3	0.872			

Note: STQ = Storytelling Quality, PV = Perceived Value, PER = Personalization, PB = Perceived Benefit, DE = Digital Engagement, PI = Purchase Intention, MO = Market Opportunity, NTT = Narrative Transportation Theory, NP = Narrative Processing, A = Affect, EE = Empathy and Emotion, MI = Mental Imagery, S = Stimulus, O = Organism, R = Response, CR = Composite Reliability, AVE = Average Variance Extracted, HTMT = Heterotrait-Monotrait. SOR and NTT serve as the underlying theoretical frameworks (SOR-NTT) for construct categorization. All measures meet statistical criteria. CR (> 0.700) and AVE (> 0.500) confirm reliability and convergent validity (27), while HTMT (< 0.850) confirms discriminant validity (33).

Results of Collinearity Assessment

To examine potential multicollinearity among predictor variables, VIF values were calculated for all structural paths in the model. Based on the results from the PLS-SEM analysis with 10,000 bootstrapping iterations. Specifically, the structural relationships STQ → PV (1.000), PER → PB (1.000), PV → DE (1.000), PB → PI (1.000) and DE → MO (1.000) all exhibited the minimum possible VIF values. These results, as shown in

Table 5, are consistent with their HTMT ratio of less than 0.900. Thus, multicollinearity is not a concern. The finding confirms that each predictor variable operates independently, without statistical redundancy. This is due to the model's structure, in which each endogenous construct is predicted by a single antecedent, thereby eliminating shared variance or competitive correlations among predictors within the SOR-NTT framework.

Table 5: Results of the Measurement Model Evaluation

Predictor → Outcome	VIF Value
STQ (Storytelling Quality) → PV (Perceived Value)	1.000
PER (Personalization) → PB (Perceived Benefit)	1.000
PV (Perceived Value) → DE (Digital Engagement)	1.000
PB (Perceived Benefit) → PI (Purchase Intention)	1.000
DE (Digital Engagement) → MO (Market Opportunity)	1.000

Note: All Variance Inflation Factor or VIF values are below the 3.000 threshold, indicating no multicollinearity issues in which highly correlated predictors obscure individual variable effects (37).

Results of Hypothesis Testing and Structural Model Evaluation

Structural model analysis using the SOR-NTT frameworks demonstrated high statistical robustness. All five hypotheses (H1–H5) were accepted, as shown in Table 6, as all relationships were statistically significant at the $p < 0.001$ level. Rather than treating statistical significance alone as evidence of practical importance, the structural relationships were interpreted using path

coefficients, effect sizes, coefficient of determination and predictive relevance. Furthermore, all pathways exhibited t-values well above the 1.96 benchmark, indicating a confidence level of over 99.9%. In particular, the DE → MO (H5) pathway had the highest t-value (15.892), indicating the clearest and most reliable relationship within the established model. Considering the direction and magnitude of the influence, the path coefficients (β) of all variables

were positive, reflecting a systematic positive relationship across the framework. The most influential pathway was DE → MO (H5) with a β of 0.724, demonstrating that digital engagement plays a crucial role in driving digital marketing opportunities. This was followed by STQ → PV (H1) with a β of 0.684 and PER → PB (H2) with a β of 0.612, highlighting that high-quality storytelling and personalization are fundamental drivers of the consumer's internal evaluation. In terms of effect size (f^2), pathway H5 exerted a strong influence ($f^2 = 1.102$), followed by H1 ($f^2 = 0.875$), both of which were categorized as large effects. Pathways H2 ($f^2 = 0.598$) and H4 ($f^2 = 0.541$) also showed substantial influence, while H3 ($f^2 = 0.429$) maintained a strong effect size, though it was the least influential of the pathways in this model. In summary, this model depicts a systematically interconnected mechanism: a high-quality stimulus (STQ and PER) that significantly affects the consumer's internal mental state (Organism: PV and PB), leading to a behavioral response (Response: DE and PI) that effectively generates business-level outcomes (MO).

Based on hypothesis testing (H1-H5), the empirical findings of this study provide a comprehensive validation of the integrated SOR-NTT framework in the context of AI-powered video marketing. The findings can be synthesized into three key stages: i) The Power of AI-Driven Stimuli (H1 and H2). Confirmation of H1 and H2 indicates that the technical attributes of AI-generated video, particularly STQ and PER, serve as potent environmental stimuli. High path coefficients ($\beta = 0.684$ and 0.612) indicate that when AI content effectively achieves NP and A, it transcends mere information and becomes an immersive

experience. This step effectively guides the audience, shifting their role from passive observers to actively engaged participants, thereby enhancing their intrinsic evaluation of the content. ii) Cognitive and Emotional Shifts (H3 and H4). The recognition of H3 and H4 highlights the crucial role of the O, the internal state in which PV and PB reside. Studies reveal that the shift from AI stimuli to behavioral intention occurs through EE and MI. The high impact magnitude ($f^2 > 0.40$) across these pathways indicates that consumers are not merely rationally evaluating AI videos. However, they also felt a connection with the videos. This storytelling process may contribute to PB, which is positively associated with PI and DE in the proposed model and iii) From Personalized Feedback to MO (H5). The most important finding is at H5, where DE shows a particularly strong impact on MO ($\beta = 0.724$, $f^2 = 1.102$). This confirms that the ultimate goal of AI marketing is not just a one-time transaction but to create a digital resonance in which consumer engagement generates a feedback loop of information and visibility. This result proves that high-quality AI storytelling not only sells products but also builds a scalable marketing ecosystem. In summary, support for all five hypotheses demonstrates that AI-generated videos are most effective when a balance is struck between technological accuracy and human-centered storytelling. Looking at the business-level scope (H5): Explains why the f^2 of H5 is highest, because it creates a brand ecosystem, not just daily sales. Maintains the core message that success lies at the intersection of AI technology and the art of storytelling. In addition, the result of the model fit evaluation is shown in Table 7.

Table 6: Result of the Hypothesis Testing and Structural Model Evaluation

Hypothesis	Path	Path Coefficient (β)	t-value	p-value	f^2	Implications
H1	STQ→PV	0.684	12.452	< 0.001	0.875	Supported (Strong)
H2	PER→PB	0.612	10.214	< 0.001	0.598	Supported (Medium-Strong)
H3	PV→DE	0.548	8.647	< 0.001	0.429	Supported (Medium)
H4	PB→PI	0.592	9.531	< 0.001	0.541	Supported (Medium-Strong)
H5	DE→MO	0.724	15.892	< 0.001	1.102	Supported (Strong)

Note: H = Hypothesis, STQ = Storytelling Quality, PV = Perceived Value, PER = Personalization, PB = Perceived Benefit, DE = Digital Engagement, PI = Purchase Intention, MO = Market Opportunity, f^2 = Effect Size.

Table 7: Result of the Model Fit Evaluation

Fit Index	Value	Implications
SRMR	0.064	Passed: Good model fit
NFI	0.912	Acceptable
d_ULS	0.845	Supported
d_G	0.512	Supported

R^2	0.618	Moderate to substantial
Q^2	0.425	Strong predictive relevance

Note: SRMR = Standardized Root Mean Square Residual, NFI = Normed Fit Index, d_ULS = Unweighted Least Squares Discrepancy, d_G = Geodesic Discrepancy, R^2 = Coefficient of Determination, Q^2 = Predictive Relevance.

Table 7 presents a comprehensive model fit assessment, confirming that the structured model fits the empirical data well. The SRMR was calculated to be 0.064, which is well below the 0.08 threshold (38). This result indicates a low discrepancy between the observed and estimated correlation matrices, demonstrating good model fit. Similarly, the NFI reached 0.912, exceeding the recommended threshold of 0.80 (38). This indicates an acceptable fit, showing that the model's ability to describe the data's relationships is significantly superior to that of a blank model. The precise fit test was further verified through the d_ULS and d_G indices. The analysis yielded values of 0.845 and 0.512, respectively. Both indices are within the acceptable range. Since these results remain below the conservative benchmark of 0.95 (35), this confirms that the model is free of significant structural bias and effectively captures the data's covariance structure. In terms of predictive capability, the model exhibits high performance. The R^2 (coefficient of determination) value is 0.618, which is classified as medium to high as it is significantly higher than the benchmark of 0.26 (30), indicating that the independent variables within the SOR and NTT framework can explain approximately 61.8% of the variance in the outcome variables. Furthermore, the Q^2 (predictive relevance) value is 0.425, which exceeds the benchmark of 0.35 (30). This confirms a medium-to-high level of predictive relevance, demonstrating the model's accuracy in predicting data points outside the current sample. In summary, the structural model has met all key criteria for fit and predictive capability. These findings confirm that the model provides a robust, reliable and highly capable framework for describing the complex relationship between AI-generated video stimuli and consumer behavioral responses.

The model fit and predictive power analysis revealed significant construct validity and model fit. The SRMR (0.064) and NFI (0.912) values indicate excellent alignment with actual consumer behavior, as demonstrated by the research framework integrating SOR and NTT theories. An SRMR value below 0.08 indicates minimal discrepancies between the model and the raw data,

while an NFI value above 0.90 suggests the model significantly outperforms the baseline in explaining the phenomena. Furthermore, the d_ULS and d_G values that meet the criteria in other study (33) reinforce the accuracy and bias-free statistical nature of the researcher's defined relationship structure for the variables. The model's coefficient of determination ($R^2 = 0.618$) is particularly noteworthy. This demonstrates that the independent variables in the Stimulus group (narrative quality and personalization) and the Organism group (PV and PB) can collectively explain 61.8% of the variance in marketing outcomes. According to the criteria (30), a value higher than 0.26 is considered to have moderate to substantial predictive power. This result indicates that the selected factors are indeed influential on consumer purchasing decisions and engagement in the digital world. Furthermore, the model's predictive relevance ($Q^2 = 0.425$), which exceeds the 0.35 threshold, confirms that it is not merely overfitting but is of sufficiently high quality to accurately predict future consumer behavior trends or those of similar target groups. The substantial Q^2 level indicates that the NTT process via AI video is a stable mechanism and can be effectively applied to predict marketing returns. In summary, this integrated SOR-NTT model is complete in both the dimensions of fit and predictive power, confirming the strength of the research framework that high-quality storytelling and personalized content tailored to consumers through AI technology are not merely temporary perceptions, but can systematically and reliably stimulate internal psychological mechanisms of consumers, leading to behavioral responses and marketing opportunities with a high level of statistical reliability.

Figure 3 presents a Full PLS-SEM model that systematically integrates the SOR-NTT concept framework. The model structure is arranged from left to right, starting with the Stimulus (S) group, namely STQ and PER, which act as stimuli; moving to the Organism (O) group, namely PV and PB, which reflect consumer perceived evaluation processes; then connecting to the Response (R) group, namely DE and PI; and finally extending to the Outcome Extension, Market Opportunity (MO),

which represents the market-level outcome. The model clearly shows causal paths, includes hypotheses H1–H5 and displays path coefficients (β) and p-values confirming statistical significance across all paths.

The structural relationships show a coherent progression from stimulus to organismic evaluation and response. STQ was associated with PV ($\beta = 0.684$) and PER was associated with PB ($\beta = 0.612$). PV was associated with DE ($\beta = 0.548$), while PB was associated with PI ($\beta = 0.592$). This indicates a significant transition from perception to response behavior and indicates that PI is also indirectly influenced by DE ($\beta = 0.284$). Finally, DE is positively associated with MO ($\beta = 0.724$), with a large effect size ($f^2 = 1.102$), indicating a substantial relationship between digital engagement and market opportunity. Overall, the SOR-NTT model can fully and effectively explain both internal perception processes and external consumer behavior in the context of digital media and AI-generated content.

Structural model analysis showed that both Stimulus (S) components, STQ and PER, had significant positive relationships with the Organism (O) components, represented by PV and PB, respectively. These factors exhibited significantly high path coefficients ($\beta = 0.684$ and 0.612). This phenomenon reflects the ability of high-quality content design and AI-driven personalization to effectively enhance consumers' psychological states and perceptions. This aligns with the SOR-NTT concept and with modern studies indicating that highly personalized, AI-driven content elicits stronger emotional responses than generic content. Furthermore, the high factor loading values of the NP and EE indicators support their measurement of the fluid narrative state. This finding is consistent with the theoretical perspective that narrative processing may facilitate psychological involvement and receptivity to the conveyed message.

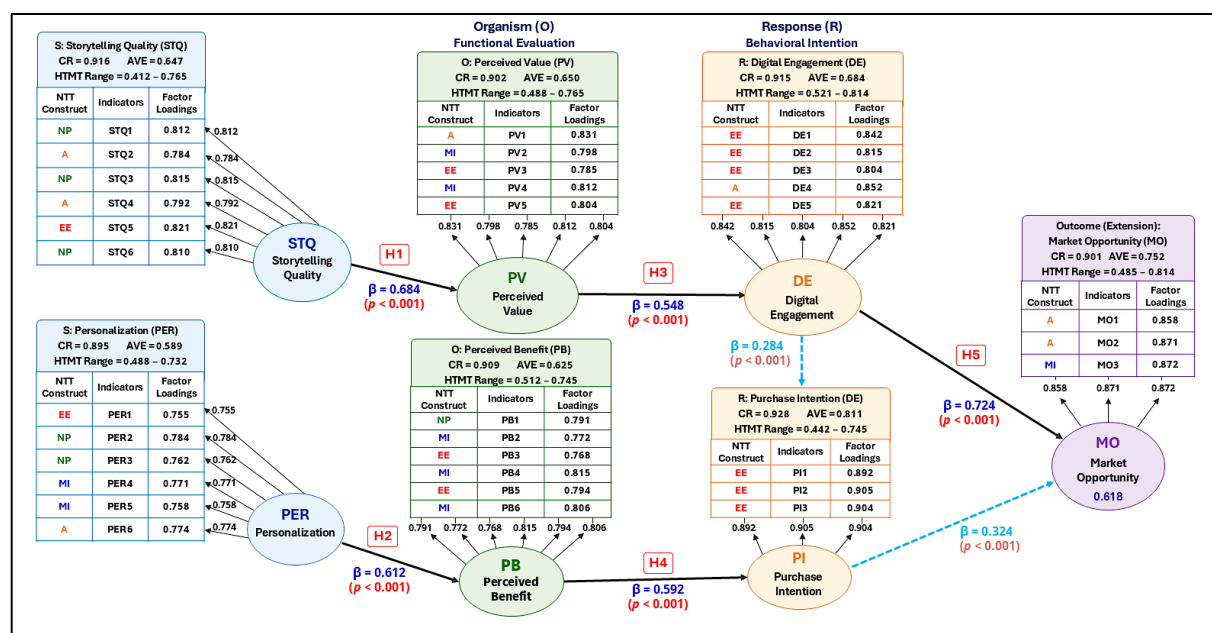


Figure 3: Result of the Full PLS-SEM Model by SOR-NTT Concept

Note: H = Hypothesis, CR = Composite Reliability, AVE = Average Variance Extracted, HTMT = Heterotrait–Monotrait.

Regarding the link from O to R and the Outcome Extension, the model reveals a powerful causal mechanism: PV directly affects DE ($\beta = 0.548$) and PB affects PI ($\beta = 0.592$). These data indicate that when consumers evaluate value and benefits through digital experiences, both behavioral (engagement) and intentional (purchase) responses occur. This aligns with recent digital marketing research, which finds that perceived value is the central variable driving the shift from interest to action.

Most interestingly, MO demonstrates a substantial positive effect in the model ($\beta = 0.724, f^2 = 1.102$), indicating a strong positive relationship between digital engagement and digital market opportunities. This finding suggests that digital engagement may play an important role in shaping digital market opportunities and may contribute to firms' longer-term competitive positioning. The

finding is broadly consistent with the Customer Engagement Value theory in the context of the digital economy.

Overall, the empirical evidence supports the proposed structural sequence but does not justify treating NTT dimensions as separately estimated causal mechanisms. The contribution of NTT in this study is theoretical. It explains how narrative characteristics such as attention, affective engagement and mental imagery may facilitate the psychological processing of AI-generated storytelling before consumers form value and benefit evaluations.

Discussion

The findings provide empirical support for the proposed SOR sequence and offer a more specific interpretation of how NTT complements that sequence. The key theoretical contribution is not the simple combination of two theories, but the specification of a narrative-to-evaluation-to-behavior mechanism. In this mechanism, AI-generated storytelling characteristics operate as external stimuli, while narrative processing, affective involvement and mental imagery provide the theoretical psychological mechanism. PV and PB represent organismic evaluations and DE and PI represent behavioral responses. This interpretation is consistent with research showing that storytelling can shape consumer experience and engagement (7, 8, 20), while narrative persuasion research indicates that transportation-related processes can support favorable consumer responses in social-media environments (24-26). H1 provides the clearest evidence for the narrative-to-evaluation link. STQ had a strong positive association with PV ($\beta = 0.684$; $f^2 = 0.875$). This result aligns with prior work showing that effective stories can strengthen consumer experience and persuasive response (8, 20) and with research emphasizing narrative transportation and immersion in digital storytelling (16, 24). The present finding extends that literature by locating perceived value immediately after the storytelling stimulus in the SOR sequence. In the sea salt context, this may reflect the fact that a coherent, culturally meaningful and emotionally engaging story can make a traditional commodity appear more distinctive and meaningful. Importantly, because narrative transportation was not directly measured as a latent variable, the data support the

STQ $\rightarrow$ PV relationship but do not establish transportation as a statistical mediator.

H2 also supports the importance of relevance in AI-mediated storytelling. PER was positively associated with PB ($\beta = 0.612$; $f^2 = 0.598$), suggesting that content aligned with consumers' interests and needs can strengthen evaluations of product usefulness and benefits. This finding complements the broader literature on AI-enabled marketing and digital personalization (13-15) by showing that PE can operate at the organismic-evaluation stage rather than only at the level of exposure or attention. H3 and H4 further show that internal evaluations are associated with subsequent responses: PV was positively associated with DE ($\beta = 0.548$; $f^2 = 0.429$), while PB was positively associated with PI ($\beta = 0.592$; $f^2 = 0.541$). These findings are compatible with the SOR proposition that internal evaluations precede behavioral responses. Because the study is cross-sectional and self-reported, however, the relationships should be interpreted as model-supported associations rather than definitive causal effects.

H5 indicates a substantial positive relationship between DE and MO ($\beta = 0.724$; $f^2 = 1.102$). This result is consistent with the view that engagement can create value beyond an immediate purchase through sharing, commenting, recommendations and increased digital visibility. The finding extends the SOR sequence by treating engagement as a response that may have consequences at an extended market level. However, MO was measured as perceived visibility, digital access and business opportunity rather than observed sales, market share, or revenue. Accordingly, the result should be interpreted as evidence of a perceived digital-market mechanism rather than direct evidence of commercial performance. The integrated framework therefore offers a more precise theoretical explanation than either theory alone. SOR explains the ordered transition from external stimulus to internal evaluation and behavioral response, while NTT explains why narrative characteristics may become psychologically influential during stimulus processing. Technological capability should consequently be viewed as an enabling condition rather than a sufficient explanation for marketing effectiveness. Cumulatively, this research suggests that AI-generated storytelling videos are most effective

when technological sophistication is combined with engaging storytelling design and meaningful personalization. Such content enhances consumer perception of value and benefits, strengthens digital engagement and purchase intent and ultimately creates opportunities in digital markets. Thus, this study underscores the importance of balancing AI capabilities with human-centered storytelling principles to maximize marketing effectiveness in the contemporary digital ecosystem.

Theoretical Implications

The study contributes theoretically by specifying the role of NTT as a psychological processing mechanism within an SOR structure rather than treating narrative transportation as an unmeasured statistical mediator. The resulting narrative-to-evaluation-to-behavior mechanism clarifies how AI-generated storytelling can move from external content characteristics to consumer evaluations and behavioral responses. The findings also distinguish storytelling quality from personalization because they connect to different organismic evaluations in the proposed model.

Practical Implications

For content developers and community enterprises, the findings indicate that AI-generated videos should prioritize coherent storytelling, cultural relevance, emotional engagement and perceived relevance to the viewer rather than relying on AI production capability alone. For digital marketers, the strong DE → MO relationship suggests that content strategies should encourage meaningful interaction, sharing, recommendation and channel participation. For community-based sea-salt producers, AI can be considered a communication tool that helps translate local knowledge into accessible digital narratives, while human oversight remains important for cultural accuracy and authenticity.

Limitations and Future Research

The study has several limitations. First, narrative transportation was theorized but not directly measured as a separate latent construct; future research should include an established narrative-transportation scale and test its mediating role directly. Second, the sample comprised 125 Thai consumers and was not designed for demographic multi-group comparison; future studies comparing demographic or consumer segments should establish measurement invariance before

interpreting group differences. Third, the cross-sectional self-report design limits causal inference. Longitudinal and experimental studies comparing AI-generated, human-generated and hybrid storytelling could provide stronger causal evidence. Fourth, market opportunity was operationalized through perceived digital-market outcomes rather than observed sales or financial performance. Finally, sustainability was not directly measured. Future research should operationalize environmental, social and economic sustainability outcomes to determine whether AI-enabled cultural marketing produces measurable sustainability benefits. These directions would help distinguish conceptual implications from empirically demonstrated outcomes.

Conclusion

This study examined how AI-generated storytelling characteristics are associated with consumer evaluations, behavioral responses and digital market opportunity for Thai sea salt in Samut Songkhram, Thailand. By integrating SOR theory with NTT, the study specified a narrative-to-evaluation-to-behavior mechanism in which storytelling quality and personalization function as stimuli, perceived value and perceived benefit represent organismic evaluations and digital engagement and purchase intention represent responses. PLS-SEM results from 125 participants supported all five hypothesized relationships. Storytelling quality was positively associated with perceived value ($\beta = 0.684$; $f^2 = 0.875$), personalization with perceived benefit ($\beta = 0.612$; $f^2 = 0.598$), perceived value with digital engagement ($\beta = 0.548$; $f^2 = 0.429$), perceived benefit with purchase intention ($\beta = 0.592$; $f^2 = 0.541$) and digital engagement with market opportunity ($\beta = 0.724$; $f^2 = 1.102$). The model explained 61.8% of the variance and showed predictive relevance ($Q^2 = 0.425$).

The findings indicate that effective AI-generated storytelling should be understood as more than a technological production process. Its potential value depends on how storytelling quality and personalization are processed by viewers and translated into meaningful product evaluations and subsequent engagement. In particular, the pathway from storytelling quality through perceived value and digital engagement to digital marketing opportunity (STQ → PV → DE → MO) highlights the interconnected role of narrative

quality, consumer value perceptions and engagement in shaping the digital marketing opportunity construct examined in this study. This suggests that producing high-quality AI-generated storytelling alone may not be sufficient to generate meaningful marketing responses; rather, effective AI communication may need to create value and engagement through consumers' cognitive and affective evaluations. However, the present study does not directly measure narrative transportation or environmental, social and economic sustainability outcomes. NTT therefore serves as a theoretical explanation of the psychological processing mechanism underlying the proposed relationships, while sustainability should be regarded as a conceptual implication that requires direct empirical assessment in future research.

Abbreviations

None.

Acknowledgement

The authors express their gratitude to the Institute for Research and Development of Suan Sunandha Rajabhat University and the National Science, Research and Innovation Fund (NSRF) for their support and the opportunity to conduct this research.

Author Contributions

Sumitra Nuanmeesri: Conceptualization, Objectives Definition, Planning and Project Administration, Hypothesis Definition, Scope Definition, Data Collection, Instrument Definition, Methodology, Data Analysis, Validation, Conclusion, Funding Acquisition, Writing – Original Draft, Writing, Review and Editing, Lap Poomhiran: Data Collection, Technical Support, Data Management, Analysis of Results, Interviews or Observations, Summary of Interview or Observation Results, Visualization, Data Analysis, Instrument Definition, Validation, Conclusion, Writing, Review and Editing, Shutchapol Chopvitayakun: Data Collection, Community Engagement, Instrument Definition, Data Analysis, Analysis of Results, Interviews or Observations, Summary of Interview or Observation Results, Validation, Conclusion, Writing, Review and Editing, Preedawon Kadmateekarun: Visualization, Data Analysis, Instrument, Definition, Validation, Analysis of Results, Interviews or Observations, Summary of Interview or Observation Results, Conclusion,

Literature Review, Writing, Review and Editing. All authors approve the final version of the manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest related to the research conducted for this study.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

During the preparation of this work, the authors utilized Gemini and ChatGPT to refine the academic writing style, enhance readability and generate technical data visualization. Following the use of these tools, the authors reviewed and edited the content to ensure academic accuracy in accordance with the research methodology and assumes sole responsibility for the content of this publication.

Ethics Approval

This study was approved by the Ethics Committee for Suan Sunandha Rajabhat University (Ref. No. COE. 2-603/2025).

Funding

The Research on Factors Influencing Ai-Generated Storytelling to Engagement in Digital Market Opportunity for Sea Salt, Samut Songkhram, Thailand by Suan Sunandha Rajabhat University has received funding support from “the National Science, Research and Innovation Fund” or “NSRF” budget for 2026. The project was carried out under grant/contract number 14705/2569.

References

1. Plaiphum S, Tansuchat R. Cultural capital of sea salt farming in Ban Laem District of Phetchaburi Province as per the Globally Important Agricultural Heritage Systems (GIAHS). Sustainability. 2023;15(15):11947. doi:10.3390/su151511947
2. Tansuchat R. A copula-based meta-stochastic frontier analysis for comparing traditional and HDPE geomembranes technology in sea salt farming among farmers in Phetchaburi, Thailand. Agriculture. 2023;13(4):802. doi:10.3390/agriculture13040802
3. Schniter E, Wilcox NT, Beheim BA, Kaplan HS, Gurven M. Information transmission and the oral tradition:

- Evidence of a late-life service niche for Tsimane Amerindians. *Evol Hum Behav.* 2018;39(1):94–105. doi:10.1016/j.evolhumbehav.2017.10.006
4. Metwally HIM, Salman SA, El-Shamy AM. A review on extraction processes of salts from different salt lakes and their environmental impact in industry. *Lett Appl Nanobiosci.* 2022;11(4):4016–4039. doi:10.33263/LIANBS114.40164039
 5. Vats S, Lakshyashree, Khan N, Jain M, Ali K. Analysing the therapeutic potential of Epsom salt across multiple human physiological systems: A comprehensive review. *J Clin Diagn Res.* 2024;18(9):KE01–KE03. doi:10.7860/JCDR/2024/72825.19979
 6. Dao TK, Nguyen TT, Vu NT. A review on the role of sea salt in food and its applications for human health. *Mini Rev Org Chem.* 2025;22(2):214–225. doi:10.2174/0118756298273343231128062213
 7. Nicoli N, Henriksen K, Komodromos M, Tsagalas D. Investigating digital storytelling for the creation of positively engaging digital content. *EuroMed J Bus.* 2022;17(2):157–173. doi:10.1108/emjb-03-2021-0036
 8. Lundqvist A, Liljander V, Gummerus J, van Riel A. The impact of storytelling on the consumer brand experience: The case of a firm-originated story. *J Brand Manag.* 2013;20(4):283–297. doi:10.1057/bm.2012.15
 9. Nechaeva O, Dasmi C. AI storytelling for global consumers: Does it improve luxury brand experience and what is the role of culture?. *Int Mark Rev.* 2026;43(7):25–49. <https://doi.org/10.1108/IMR-04-2025-0200>
 10. Choi YJ, Kenney L. A conceptual framework to explore considerations of the social implications in internet of things and smart city governance and policy: The case of Thailand. *Policy & Internet.* 2024;16(2):242–271. doi:10.1002/poi3.401
 11. Taeratanachai C, Lekhsul C. Factors affecting purchase intention of TikTok social commerce in Thailand. *J Family Bus Manag Stud.* 2026;18(1):171–188. https://www.fbmsjournal.com/wp-content/uploads/2026/01/10_User-89_Factors-Affecting-Purchase-Intention-of-TikTok-Social-Commerce-in-Thailand.pdf
 12. Tariq MU. The influence of AI on digital storytelling and media narratives. *Digital and cultural influences on media narratives and storytelling*, New York: IGI Global Scientific Publishing. 2025;1–26. doi:10.4018/979-8-3373-2023-6.ch001
 13. Huang MH, Rust RT. A strategic framework for artificial intelligence in marketing. *J Acad Mark Sci.* 2021;49(1):30–50. doi:10.1007/s11747-020-00749-9
 14. Davenport T, Guha A, Grewal D, Breussgott T. How artificial intelligence will change the future of marketing. *J Acad Mark Sci.* 2020;48(1):24–42. doi:10.1007/s11747-019-00696-0
 15. Anantrasirichai N, Bull D. Artificial intelligence in the creative industries: A review. *Artif Intell Rev.* 2022;55(1):589–656. doi:10.1007/s10462-021-10039-7
 16. Sung EC, Han DID, Bae S, Kwon O. What drives technology-enhanced storytelling immersion? The role of digital humans. *Comput Human Behav.* 2022;132:107246. doi:10.1016/j.chb.2022.107246
 17. Antony VN, Huang CM. ID.8: Co-creating visual stories with generative AI. *ACM Trans Interact Intell Syst.* 2024;14(3):1–29. doi:10.1145/3672277
 18. Bervar M, Bertoncel T, Pejić Bach M. Generative artificial intelligence and the creative industries: A bibliometric review and research agenda. *Systems.* 2026;14(2):138. doi:10.3390/systems14020138
 19. Spennemann DHR. Generative artificial intelligence, human agency and the future of cultural heritage. *Heritage.* 2024;7(7):3597–609. doi:10.3390/heritage7070170
 20. Mandung F. The influence of storytelling techniques in digital marketing on brand loyalty: A consumer psychology perspective. *Golden Ratio Mark Appl Psychol Bus.* 2024;5(1):66–78. doi:10.52970/grmapb.v5i1.782
 21. Hasanein AM, Al-Romeedy BS, Khairy HA, Thani AMA. AI-driven cultural storytelling and tourists' behavioral intentions: Understanding the mediation of authenticity and destination image. *Heritage.* 2026;9(2):78. doi:10.3390/heritage9020078
 22. Dalvi-Esfahani M, Barati-Ahmadabadi H, Ramayah T, Turner JJ, A. Iahad N, Azar N. Stimulus-organism-response framework of decision-makers intention to adopt generative AI to replace entry-level jobs: The moderating impact of personality traits. *Technol Forecast Soc Change.* 2025;219:124291. doi:10.1016/j.techfore.2025.124291
 23. Chen L, Wu X, Liu Y, Hu Z, Chen X, Zhang Z. Integrating TAM-ISSM-SOR framework to explore how virtual tourism experience influences tourists' travel intention. *Sci Rep.* 2025;15:38826. doi:10.1038/s41598-025-24793-z
 24. Huang R, Ha S, Kim SH. Narrative persuasion in social media: An empirical study of luxury brand advertising. *J Res Interact Mark.* 2018;12(3):274–292. doi:10.1108/JRIM-07-2017-0059
 25. Boeck H, Bourguignon B, Saravani SHH, Bahra M. Evaluating the impact of storytelling elements on social media stakeholder engagement: An AI-driven approach. *Data Policy.* 2025;7:e62. doi:10.1017/dap.2025.10029
 26. Tan SZ, Yang L, Loo WH, Chalke A. Stories that matter: the effects of narrative transportation and influencer-message congruity on prosocial behavior. *J Bus Res.* 2026;208:116051. doi:10.1016/j.jbusres.2026.116051
 27. Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. *Eur Bus Rev.* 2019;31(1):2–24. doi:10.1108/eb-11-2018-0203
 28. Kock N, Hadaya P. Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Inf Syst J.* 2016;28(4):227–261. doi:10.1111/isj.12131
 29. Tripopsakul S, Hoonsopon D. Influencer credibility, parasocial relationships and product involvement in purchase intentions. *Emerg Sci J.* 2025;9(4):2132–

2144.
doi:10.28991/ESJ-2025-09-04-021
30. Nuanmeesri S. Developing gamification to improve mobile learning in Web Design course during the COVID-19 pandemic. *Int J Inf Educ Technol.* 2021;11(12):567–573.
doi:10.18178/ijiet.2021.11.12.1566
 31. Soeprapto EF, Partiwi SG, Widyaningrum R. Synergizing innovation: Examining the TOE readiness influence, ambidextrous capabilities, organization resilience on craft SMEs. *Emerg Sci J.* 2026;10(1):559–576.
doi:10.28991/ESJ-2026-010-01-028
 32. Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. *J Mark Res.* 1981;18(1):39–50.
doi:10.2307/3151312
 33. Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J Acad Mark Sci.* 2014;43(1):115–135.
doi:10.1007/s11747-014-0403-8
 34. Dash G, Paul J. CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technol Forecast Soc Change.* 2021;173(3):121092.
doi:10.1016/j.techfore.2021.121092
 35. Schuberth F. Confirmatory composite analysis using partial least squares: Setting the record straight. *Rev Manag Sci.* 2021;15(5):1311–1345.
doi:10.1007/s11846-020-00405-0
 36. Hair JF, Alamer A. Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Res Methods Appl Linguist.* 2022;1(3):100027.
doi:10.1016/j.rmal.2022.100027
 37. Diamantopoulos A, Siguaw JA. Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. *Br J Manag.* 2006;17(4):263–282.
doi:10.1111/j.1467-8551.2006.00500.x
 38. Hu LT, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct. Equation Modell. Multidiscip. J.* 1999;6(1):1–55.
doi:10.1080/10705519909540118

How to Cite: Nuanmeesri S, Poomhiran L, Chopvitayakun S, Kadmateekarun P. Factors Influencing AI-Generated Storytelling to Engagement in Digital Market Opportunity for Sea Salt, Samut Songkhram, Thailand. *Int Res J Multidiscip Scope.* 2026;7(4):1453-1471. DOI: 10.47857/irjms.2026.v07i04.012635