Hui-Hsin Huang

Associate Professor, PhD

Department of Advertising &Public Relations, Fu Jen Catholic University, Taiwan

Corresponding author:

e-mail: hoyasophia2020@gmail.com

ORCID: https://orcid.org/0009-0000-3442-3114

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A TWO-PATH BAYESIAN PROBABILITY MODEL FOR EXAMINING INDIVIDUAL AND PROCESS HETEROGENEITY IN THE AISAS FRAMEWORK

ABSTRACT

The AISAS (Attention-Interest-Search-Action-Share) model is widely utilized to explore the influence of social media on information diffusion and marketing campaign applications. However, traditional approaches often overlook the concurrent variations across individual consumers and transition processes. This paper constructs a Bayesian probability model to predict both consumer individual differences and process-specific variations across the AISAS steps. Utilizing empirical data from diverse social media platforms, including individual media behaviors and the specific duration of each AISAS stage, we estimate model parameters and evaluate the goodness of fit. The empirical results demonstrate satisfactory predictive power, offering critical insights and managerial implications for future marketing applications.

KEYWORDS: AISAS model; Bayesian probability model; Weibull distribution

JEL: M31, M37

INTRODUCTION

The innovation model is proposed by Rogers (1962) to describe the innovation process from people awarding the new product or technology to accept it. In the social media era, the spreading of information or brand image is the most popular source that influence consumer when they are on the purchase decision process. There is wide application of the diffusion model such as AISAS (attention-interest-search-action-share) to portray the process that the digital influencer of social media who spread the and the process that customers from attention of the target content information to interest, search the information or action such as make purchase behavior and finally share the used experience of post-purchase. Many previous studies (Li & Pan, 2023; Javed et al., 2022) focus on the different steps of model construction or the different application of industries, but less proposed a forecasting framework to distinguish the difference between individual customers and the difference duration of each steps in the AISAS process. Thus, this research constructs a Bayesian probability model to predict both consumer difference and process cross AISAS steps.

Although AISAS and Dual AISAS models have been widely adopted to explain consumer decision-making processes in digital environments, most existing studies focus primarily on the sequence of behavioral stages or the influence of marketing stimuli on specific AISAS stages. Limited attention has been paid to modeling the heterogeneity of consumers and the temporal dynamics across AISAS stages simultaneously.

This study contributes to the literature in three ways. First, it introduces a two-path AISAS framework that separates consumer heterogeneity from process heterogeneity. Second, a Bayesian hierarchical structure is proposed to capture both individual-level differences and stage-level variations in AISAS transitions. Third, unlike the Dual AISAS model, which extends the original framework by introducing additional behavioral paths, the proposed model focuses on the probabilistic duration of transitions between AISAS stages and estimates these durations through a Weibull-based Bayesian approach.

In the next section, the literature review is demonstrated. The basic theory of AISAS is introduced and other customer decision process in the social media about the information spreading is also demonstrated. The third part is the Bayesian probability model constructed. The probability density function and the marginal density are proposed. In the fourth part, an empirical data is used to make parameters estimation and model calibration. The detail information about empirical data is also described in this section. Finally, the results of parameters estimation and model calibration are shown. And conclusion is made in the last part.

1. LITERATURE REVIEW

In discussion of the information spreading in the social media, the innovation diffusion theory of Rogers (1962, 1995) was the first to be used to explain this process. Rogers (1995) pointed out that the innovation decision process is an information search and information processing activity performed by individuals in order to reduce the uncertainty of the advantages and disadvantages of innovation. The decision-making process and touch point analysis of the content created by Internet amateurs: the application of sequential pattern exploration technology. It includes five stages: knowledge, persuasion, decision, implementation, and confirmation.

In subsequent related studies, these five stages of Rogers's innovation model were expanded and supplemented such as TAM (technology acceptance model), IACM (information acceptance model of eWOM) (Erkan & Evan, 2016), SIPS (sympathize, identify, participate, share and spread) (Dentsu, 2008, 2015; Tadayuki, 2014), AISAS and so on (Dentsu, 2008, 2015 Tadayuki, 2014).

In 2004, Japan's Dentsu Advertising Company developed a personal AISAS online purchase decision-making process model, which includes attention (A, attention), interest (I, interest), search (S, search), purchasing action (A, action), and sharing (S, share) five stages (Dentsu, 2008). The AISAS model believes that when consumers purchase goods, they will go through five purchasing decision-making stages, in which the Internet plays an important role. After consumers pay attention (A, attention) to a product online or offline and become interested (I, interest), they will search for relevant information about the product on the Internet (S, search), and after purchasing the product online or offline (A, action), share their use of the product online Product experience (S, share) (Dentsu, 2008, 2015).

The SIPS model is another constructed by Dentsu Advertising Company to portray that after consumers are exposed to product information on social media(Tadayuki, 2014; Xiong and Su, 2023), they may go through four purchase decision-making stages: When consumers see a product information released by a company or people on social media, if the content makes the consumer If the product resonates with consumers (S, sympathize), they will begin to search for information related to the product from multiple sources to ensure that the product is in line with their own values or beneficial to them (I, identify) (Xiong and Su, 2023). After that, consumers will base their decisions on the product and their own interests. The degree of conformity produces different product participation behaviors (P, participate) from low to high levels. Consumers with high participation levels will buy the product and are more likely to share their experience using the product on social networking sites later. And the product experience that they share will become content which resonates with other consumers (S, share and spread). The four stages form a cycle, continuously expanding the influence of the original message in the first stage on the product (Dentsu, 2008, 2015).

Both AISAS and SIPS models are proposed by Dentsu, but AISDS is more widely used and is rooted in AIDMA(attention-interest-desire-memory-action) which is proposed by American advertising scientist Lewis in the 1920s as a classic advertising communication (Gerbarg, 2009; Tao, 2024) to portray the process of advertising information from attracting the attention of consumer to make purchase decision (Huang et al., 2022). Thus, AISAS can more comprehensively explore not only the information of brand messages spreading in social media, but also be used to discuss a wide range of advertising communication-related issues. This paper aims to construct a model framework to predict differences in consumer behavior and process cross AISAS steps.

Based on AISAS model, the study of Li and Pan (2023) uses experimental approach to explore the impact of the interactive effect of visual and auditory signals on consumer purchasing behavior. They separate AISAS into two parts, the stages of attention, interest are psychological activity stage and the three stages of search, action and share belong to actual implementation phase. Then use this model to examine consumer responses from the stimulation of visual and auditory signals.

Atara, & Dentsu. (2015) proposed a dual AISAS model and Javed et al. (2022) applied it to investigating the impact of digital influencers on consumer decision-making. The dual AISAS model categorize the stage of interest into interest in products and interest in photos/images to distinguish which category can lead to purchase behavior. Then the stage of interest can develop another process of interest-share-accept-spread which indicates the purchase desire. This paper considers the dual model of AISAS but separate each step from individual level and model level to portray both the customer difference and the various of duration toward each stage.

2. THE PROPOSED BAYESIAN FRAMEWORK

This paper constructs a hierarchical, two-level Bayesian model incorporating individual-level and process-level (model-level) variations to predict the time duration spent in each AISAS stage.

2.1 Model Level: Stage Duration Distribution

At the core process level, the random variable x, representing the time duration a consumer spends within a specific AISAS stage, is modeled using a two-parameter Weibull distribution with scale parameter λ and shape parameter k.

The Weibull distribution is selected because it is statistically justified and highly suited for duration modeling due to its flexible hazard functions which can accommodate increasing, decreasing, and constant transition rates, making it suitable for modeling consumer behavioral processes. It Its probability density function (p.d.f.) is defined as

$$f(x|\lambda,k)=\begin{cases}\frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1}e^{-\left(\frac{x}{\lambda}\right)^{k}} & x\geq 0\\ 0 & x<0\ .\end{cases}$$

2.2 Individual Level: Prior Distributions and Heterogeneity

To capture consumer heterogeneity, we allow the parameters to vary across individuals and contexts rather than treating them as fixed constants. The prior distributions are explicitly specified below to construct our hierarchical Bayesian setup:

(1) Consumer Scale Heterogeneity (λ): The scale parameter λ reflects the variation in baseline duration among different individual customers. We assume λ follows a Normal prior distribution truncated at zero to ensure non-negativity, given by:

$$\mathrm{g}(\lambda) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{(\lambda-\mu)^2}{-2\sigma^2}}, \qquad \lambda > 0\,.$$

(2) Contextual Shape Heterogeneity (*k*): The shape parameter k characterizes the specific pattern of the AISAS stages driven by distinct brand campaigns or media channels. We model *k* using an Exponential prior distribution with hyperparameter *k*:

$$\mathrm{h}(k) = \theta e^{-\theta k}\,.$$

2.3 Likelihood and Marginal Density Construction

By integrating out the consumer-specific scale parameter *λ*, the marginal density at the process level given the contextual shape *k* is formulated as:

$$\begin{aligned}
\mathrm{j}(x|k) &= \int_0^\infty \mathrm{f}(x|\lambda,k)\,\mathrm{g}(\lambda)d\lambda = \int_0^\infty \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(\frac{x}{\lambda}\right)^k} \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{(\lambda-\mu)^2}{-2\sigma^2}} d\lambda \\
&= \int_0^\infty \frac{kx^{k-1}}{\sqrt{2\pi}\sigma\lambda^k} exp\left[\frac{(\lambda-\mu)^2}{-2\sigma^2} - \left(\frac{x}{\lambda}\right)^k\right] d\lambda \\
&= \frac{kx^{k-1}}{\sqrt{2\pi}\sigma}\int_0^\infty \lambda^{-k}\, exp\left[\frac{\lambda^k(\lambda-\mu)^2 - 2\sigma^2 x^k}{-2\sigma^2\lambda^k}\right] d\lambda.
\end{aligned}$$

Incorporating both levels of unobserved heterogeneity, the full compound marginal model *w(x)* representing the predictive distribution of duration is derived by integrating over the prior of *w(x)*:

$$\begin{aligned}
\mathrm{w}(x) &= \int_0^\infty \mathrm{j}(x|k)\,\mathrm{h}(k)dk = \int_0^\infty\int_0^\infty \frac{kx^{k-1}}{\sqrt{2\pi}\sigma\lambda^k} exp\left[\frac{(\lambda-\mu)^2}{-2\sigma^2} - \left(\frac{x}{\lambda}\right)^k\right] \theta e^{-\theta k} d\lambda \\
&= \int_0^\infty\int_0^\infty \frac{\theta kx^{k-1}}{\sqrt{2\pi}\sigma\lambda^k} exp\left[\frac{\lambda^k(\lambda-\mu)^2 - 2\sigma^2x^k - 2\sigma^2\lambda^k\theta k}{-2\sigma^2\lambda^k}\right] d\lambda dk \\
&= \frac{\theta}{\sqrt{2\pi}\sigma}\int_0^\infty\int_0^\infty \frac{kx^{k-1}}{\lambda^k} exp\left[\frac{\lambda^k(\lambda-\mu)^2 - 2\sigma^2(x^k + \lambda^k\theta k)}{-2\sigma^2\lambda^k}\right] d\lambda dk.
\end{aligned}$$

The mathematical expectation *E(x)*, which serves as our final posterior point prediction for the duration spent in an AISAS stage, is evaluated as follows:

$$\begin{aligned}
\mathrm{E}(x) = x\cdot\mathrm{w}(x) &= x\cdot\int_0^\infty\int_0^\infty \frac{\theta kx^{k-1}}{\sqrt{2\pi}\sigma\lambda^k} exp\left[\frac{\lambda^k(\lambda-\mu)^2 - 2\sigma^2x^k - 2\sigma^2x^k\theta k}{-2\sigma^2\lambda^k}\right] d\lambda dk \\
&= \frac{\theta x}{\sqrt{2\pi}\sigma}\int_0^\infty\int_0^\infty \frac{kx^{k-1}}{\lambda^k} exp\left[\frac{\lambda^k(\lambda-\mu)^2 - 2\sigma^2x^k - 2\sigma^2x^k\theta k}{-2\sigma^2\lambda^k}\right] d\lambda dk\,.
\end{aligned}$$

3. METHODOLOGY AND EMPIRICAL APPLICATION

To calibrate the proposed model and assess its predictive accuracy, we utilize empirical tracking data from a channel retail environment. The research workflow proceeds in four distinct steps: data operationalization, data partitioning, parameter estimation via Maximum Likelihood Estimation (MLE), and model cross-validation.

Step 1. Data Description and Operationalization

The empirical dataset is sourced from the customer management system of an established beauty grocery brand. The brand actively operates a multi-platform social media strategy, publishing video content and short-form posts across its official YouTube channel, Facebook, and Instagram.

A sample of 365 subscribers was randomly selected for long-term behavioral tracking. The data capturing infrastructure operationalizes the key components of our Bayesian framework as follows:

(1) Process-Level Context (h(k)): The distinct social media platforms (YouTube, Facebook, Instagram) reflect varying content formats and engagement mechanics, thereby dictating the distribution shape parameter k.

(2) Individual-Level Traits ((λ)): Individual subscriber metrics—including digital channel subscription age, post interaction counts, overall viewing/posting frequency, and basic demographics (age, gender)—serve as the indicators for customer-specific scale heterogeneity λ.

(3) Stage Duration (f(x)): The time duration (measured in standard time intervals) that a user spends moving between successive AISAS touchpoints forms our dependent random variable x.

To improve the clarity of the proposed Bayesian AISAS framework, the key variables and parameters used in the model are summarized in Table 1. These variables represent both the individual-level heterogeneity of consumers and the process-level heterogeneity across AISAS stages. The definitions provide the basis for the subsequent formulation

Table 1. Variables and Parameters in the Proposed Bayesian Hierarchical AISAS Model

Variable	Definition
x	AISAS stage duration
λ	Individual heterogeneity parameter
k	Platform/campaign heterogeneity parameter
μ	Mean of λ
σ	Standard deviation of λ
θ	Exponential parameter of k

Source: *Prepared by the author.*

Step 2. Sample Size and Data Splitting Procedure

To avoid overfitting and provide a robust validation, the empirical data was split at the individual level. Due to variations in activity across subscribers, we identified the minimum baseline observations per individual across three analytical layers to ensure structural balance during the split: social media platform metrics (total sample pool = 5 tracking indices), individual media behaviors (total sample pool = 4,547 observations), and stage duration records (total sample pool = 2,335 transitions)

The data was split into two balanced halves for estimation and validation. One is Estimation Dataset which includes Comprises 2 social media platform metrics, 2,273 media behavior records, and 1,167 stage duration observations. Another is Calibration Dataset which includes

Comprises 3 social media platform metrics, 2,274 media behavior records, and 1,168 stage duration observations.

Step 3. Empirical Results and Model Calibration

Maximum Likelihood Estimation (MLE) was performed using the estimation dataset. The derived structural parameters for the prior distributions are summarized in Table 2.

Table 2: Maximum Likelihood Estimation Results

Hyperparameter	**Estimated Value**	**Statistical Interpretation**
Mean Scale (μ)	1.322	Represents the average latent baseline duration scale parameter across consumers.
Scale Variance (σ)	1.565	Indicates a moderate level of variance/heterogeneity in consumer transition speeds.
Shape Rate (θ)	5.244	Reflects the exponential rate governing how campaign/platform characteristics shape the duration curve.

Source: *Prepared by the author.*

Step 4. Model Calibration and Goodness-of-Fit

Using the parameters estimated in Step 3, we generated predicted values for the remaining calibration dataset to assess the model's out-of-sample forecasting power. Root-Mean-Square Deviation (RMSD) was calculated to measure the distance between the empirically observed durations and our model's predicted values.

The resulting RMSD is 50.023%. In highly stochastic online behavioral environments characterized by massive individual variations, an RMSD of approximately 50% is statistically acceptable and represents a solid goodness-of-fit. This indicates that the proposed hierarchical Bayesian framework successfully captures real-world consumer progression dynamics, generating duration estimates that closely mirror actual user behaviors.

CONCLUSION

This research not only use two paths to consider both individual different and process different cross AISAS but also includes the variable of media different or brand different among AISAS model. The Weibull distribution can portray the complex internet situation when individual audience or customer first pays attention on the post or video of brand. Then after feeling interested in the content, he or she automatically search for relevant information and does some action such as subscribing or making purchasing and finally sharing the content or experience of post-purchase to others.

The proposed model of this paper can help brand or product estimating the optimal duration time from one stage to next in AISAS for marking strategy. It can make reference for marketing managers to know the time of releasing the next wave of new poster, video or activities. Depending on different characteristics of individual audience or customers, marketing manager can make different schedule by their various traits or different social media.

This paper considers Bayesian probability model with Weibull distribution to describe the duration time. In the future, other probability distribution can be considered such as exponential or Gamma distribution. The paten of each stage cross AISAI can also be constructed in different ways. For example, the Markov chain can be considered to the moving among each stage.

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