ISSN: 1983-6635

RGO Revista Gestão Organizacional

DYNAMIC CAPABILITIES IN HYPER-PERSONALIZATION: AN ANALYSIS USING STRUCTURAL EQUATION MODELING WITH CLICKSTREAM DATA

CAPACIDADES DINÂMICAS NA HIPERPERSONALIZAÇÃO: UMA ANÁLISE VIA MODELAGEM DE EQUAÇÕES ESTRUTURAIS COM CLICKSTREAM

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Editor científico: Sady Mazzioni

Submissão: 09/11/2025. Revisão: 12/03/2026. Aceite: 04/05/2026. Publicação: 05/08/2026.

Como citar: Silva, C. C. da., Gomes, M. G. S., Dantas, G. M. M. F. F., Araujo, A. G. de., & Andrade, A. P. V. de., (2026). Capacidades dinâmicas da hiperpersonalização: uma análise via modelagem de equações estruturais com clickstream. RGO - Revista Gestão Organizacional, 19(1), 158-181. http://dx.doi.org/10.22277/rgo.v19i1.8724

ABSTRACT

Purpose: To propose and validate an empirical model for measuring hyperpersonalization potential in e-commerce environments, operationalized based on browsing patterns recorded in clickstream data.

Method/approach: This is a quantitative, observational, and confirmatory study based on secondary clickstream data from an e-commerce environment. The empirical dataset comprises 74,817 browsing records from 1,000 users, aggregated into 10,000 sessions between January and July 2024. The unit of analysis was the browsing session. The data underwent preprocessing, including the exclusion of single-event sessions and the handling of outliers. The hyperpersonalization potential construct was estimated using structural equation modeling within a reflective single-factor model, with four behavioral indicators: viewing intensity, product diversity explored, proportion of views, and conversion rate. Measurement quality was assessed using factorability tests, composite reliability, extracted mean variance, and model fit indices.

Main findings: The results indicated that browsing patterns derived from clickstream data constituted empirical indicators of hyperpersonalization potential in digital environments. The model demonstrated satisfactory validity and reliability.

Theoretical, practical/social contributions: This study bridges the literature on digital behavioral data with the theory of dynamic capabilities by proposing an empirical method for measuring the behavioral foundations associated with digital personalization.

Originality/relevance: This study proposes an empirical model to measure the behavioral foundations of hyperpersonalization in digital ecosystems, linking observable patterns of online interaction to the microfoundations of dynamic capabilities.

Keywords: Hyperpersonalization. Digital personalization. Dynamic capabilities. Resource-Based View. Clickstream.

RESUMO

Objetivo: Propor e validar um modelo empírico de mensuração do Potencial de Hiperpersonalização em ambientes de *e-commerce*, operacionalizado a partir de padrões de navegação registrados em dados de *clickstream.*

Método/abordagem: Trata-se de uma pesquisa quantitativa, observacional e confirmatória baseada em dados secundários de *clickstream* em ambiente de *e-commerce*. A base empírica reúne 74.817 registros de navegação de 1.000 usuários, agregados em 10.000 sessões entre janeiro e julho de 2024. A unidade analítica foi a sessão de navegação. Os dados passaram por pré-processamento, incluindo exclusão de sessões com evento único e tratamento de *outliers*. O construto Potencial de Hiperpersonalização foi estimado por Modelagem de Equações Estruturais em um modelo reflexivo de fator único com quatro indicadores comportamentais: intensidade de visualizações, diversidade de produtos explorados, proporção de visualizações e taxa de conversão. A qualidade da mensuração foi avaliada por testes de fatorabilidade, confiabilidade composta, variância média extraída e índices de ajuste do modelo.

Principais Resultados: Os resultados indicam que padrões de navegação derivados de dados de *clickstream* constituem indicadores empíricos do potencial de hiperpersonalização em ambientes digitais. O modelo apresentou validade e confiabilidade satisfatórias.

Contribuições teóricas/práticas/sociais: O estudo aproxima a literatura de dados comportamentais digitais da teoria das capacidades dinâmicas ao propor uma forma empírica de mensurar fundamentos comportamentais associados à personalização digital.

Originalidade/relevância: O estudo propõe um modelo empírico para mensurar as bases comportamentais da hiperpersonalização em ecossistemas digitais, conectando padrões observáveis de interação online aos microfundamentos das capacidades dinâmicas.

Palavras-chave: Hiperpersonalização. Personalização digital. Capacidades dinâmicas. Visão Baseada em Recursos. *Clickstream*.

1 INTRODUCTION

E-commerce has undergone significant transformation in recent decades, evolving from a supplementary sales channel into a digital ecosystem characterized by the intensive use of data to inform strategic decision-making (Kannan & Li, 2017).

Understanding consumer behavior is no longer exclusively reliant on retrospective analyses based on market research, sales history, and customer feedback (Davenport, 2023). With the expansion of dynamic, information-rich digital markets, consumers now demand more relevant and personalized experiences, shifting organizations' competitive focus toward interpreting behavioral cues and responding to individual needs in real time (Laudon & Traver, 2024).

In this context, digital personalization has emerged as a mechanism for competitive differentiation in online environments (Rochefort & Ndlovu, 2024). Digital personalization typically refers to the process of tailoring content, recommendations, or offers based on historical data or users' behavioral patterns, thereby adapting consumer experiences to preferences identified throughout digital interactions (Bleier et al., 2017; Vesanen & Raulas, 2006).

By reducing uncertainty in the purchasing journey and providing more relevant interactions, digital personalization strategies have been associated with higher engagement, satisfaction, and conversion rates in digital environments (Lemon & Verhoef, 2016).

Recent advances in data usage and analytical capabilities have expanded the possibilities of digital personalization, enabling more precise and dynamic adaptations in consumer interactions (Chandra et al., 2022). In recent literature, this development is characterized as hyper-personalization (Davenport, 2023; Guendouz, 2024; Rane, Choudhary, & Rane, 2023; Sipos, 2024; Srivastav, 2025; Narayana & Koralla, 2025).

Unlike traditional digital personalization, which relies mainly on segmentation or aggregated historical patterns, hyper-personalization involves the continuous adaptation of interactions between companies and consumers. This adaptation integrates multiple sources of behavioral, emotional, contextual, and historical data, enabling ongoing, real-time adjustments throughout digital interactions (Davenport, 2023; Jain et al., 2021; Narayana & Koralla, 2025; Rane, Choudhary, & Rane, 2023; Sipos, 2024; Srivastav, 2025; Valdez Mendia & Flores-Cuautle, 2022).

Although the recent literature has advanced in describing the technologies and applications associated with hyper-personalization, many studies remain primarily focused on technological aspects or operational performance metrics, such as algorithmic accuracy, conversion rates, and engagement levels (Davenport, 2023; Jain et al., 2021; Valdez Mendia & Flores-Cuautle, 2022; Rane, Choudhary, & Rane, 2023; Sipos, 2024; Srivastav, 2025; Narayana & Koralla, 2025). Research aimed at understanding and empirically measuring the behavioral and analytical foundations underlying this phenomenon in digital environments remains limited.

Before the advent of current hyper-personalization practices, clickstream data had already been widely used in marketing research to map browsing patterns, assess website engagement, and predict online purchasing behavior (Bucklin et al., 2002; Kagan & Bekkerman, 2018; Olbrich & Holsing, 2011; Pal et al., 2021; Raphaeli et al., 2017; Su & Chen, 2015).

Analyses of click sequences, dwell times, and navigation paths have enabled researchers to understand patterns of interest and various stages of the purchase journey at both the aggregate and session levels (Bucklin & Sismeiro, 2009; Montgomery et al., 2004), establishing analytical foundations that later contributed to the development of advanced personalization strategies.

Consequently, clickstream data facilitate the analysis of how consumers interact with digital environments and how these interactions can be translated into data-driven strategic decisions.

From a business strategy perspective, such data can be viewed as strategic resources that sustain competitive advantage. The resource-based view asserts that valuable, rare, and difficult-to-imitate resources can form the basis of sustainable competitive advantage (Barney & Hesterly, 2007; Wernerfelt, 1984).

In the digital context, behavioral data, analytical infrastructure, and data interpretation capabilities become vital strategic assets for value creation. However, the strategy literature emphasizes that in dynamic environments, value creation depends on organizations' capacity to interpret, integrate, and mobilize resources through organizational capabilities that enable continuous adaptation to changes in the competitive environment (Sun, Chen, & Mei, 2024; Teece, Pisano, & Shuen, 1997).

Dynamic capabilities theory posits that competitive advantage in settings of rapid technological transformation depends on organizational ability to detect emerging opportunities (sensing), mobilize resources to exploit them (seizing), and continually reconfigure organizational processes and routines (reconfiguring) (Eisenhardt & Martin, 2000; Teece, 2007).

Although recommendation systems and analytical models based on digital interaction data have advanced, much of the literature focuses on algorithmic effectiveness or operational marketing metrics such as conversion rates or engagement (Davenport, 2023; Jain et al., 2021). Research attempting to link observable behavioral patterns in digital environments to broader strategic processes related to organizational capabilities remains limited.

Based on these considerations, we propose that observable digital interaction patterns in clickstream data provide relevant behavioral signals about consumer interactions with digital platforms. These signals serve as informational inputs for analytical routines employed by organizations to detect and exploit opportunities in digital environments. Therefore, the ability to interpret and leverage such data is a component of the organizational capabilities required to implement hyper-personalization practices.

From this perspective, we argue that current hyper-personalization practices represent the evolution of analytical routines developed through the interpretation of behavioral signals generated in digital interactions. To investigate this proposition, this study utilizes an e-commerce database containing browsing and transaction records from January through July 2024, enabling the analysis of behavioral patterns associated with personalization in digital environments.

Within this framework, this study aimed to propose and validate an empirical model to measure the behavioral foundations of hyper-personalization in e-commerce environments, operationalized through browsing patterns captured in clickstream data. Specifically, it sought to explore how these patterns can serve as empirical indicators associated with the processes of sensing and seizing opportunities.

Theoretically, this study contributes by bridging the gap between behavioral data and the strategy literature, demonstrating how observable metrics of digital interaction can be used to measure strategic processes connected to dynamic capabilities. In practice, the proposed model provides an analytical tool to help managers assess the maturity of analytical and personalization capabilities in digital environments. Additionally, by employing observational browsing data, the study advances the development of replicable methodological approaches for investigating strategic phenomena in data-driven digital ecosystems.

The article is structured into five sections. Section 2 presents a literature review on digital personalization, hyper-personalization, e-commerce, and dynamic capabilities. Section 3 describes the methodological procedures adopted, emphasizing the use of structural equation modeling (SEM) applied to clickstream data. Section 4 presents the empirical results of the proposed model. Lastly, Section 5 discusses the theoretical and managerial implications of the study, along with its limitations and suggestions for future research.

2 LITERATURE REVIEW

2.1 PERSONALIZATION AND ITS EVOLUTION TOWARD HYPER-PERSONALIZATION

The evolution of personalization in marketing originated with early approaches to market segmentation. Smith (1956) proposed that markets could be divided into relatively homogeneous subgroups, enabling organizations to target their offerings and communications more efficiently. These segments are defined using various variables, such as demographic criteria (e.g., age, gender, and income), geographic criteria (e.g., location and climate), psychographic criteria (e.g., lifestyle, values, and personality), and behavioral criteria (e.g., frequency of use, brand loyalty, and desired benefits).

This logic was subsequently consolidated into the segmentation, targeting, and positioning framework, which is widely applied in strategic marketing literature to identify priority segments and develop targeted value propositions (Kotler & Keller, 2016). Over the following decades, marketing increasingly integrated data into customer relationship strategies. Direct marketing, formalized by Wunderman (1973), combined segmentation with the use of structured databases (i.e., though initially limited in their analytical capability) to establish direct communication with consumers (Peelen, Ekelmans & Vijn, 1989; Sheth & Parvatiyar, 1995).

Relationship marketing, introduced by Berry (1983), highlighted the significance of building enduring customer relationships. This evolution culminated in one-to-one marketing, popularized by Peppers and Rogers (1993), which advocated treating each customer individually based on information gathered throughout their interactions. Simultaneously, advancements in operations management enabled mass customization, a concept introduced by Davis (1987) and later consolidated by Pine (1993). This approach allowed tailoring products to individual preferences while preserving economies of scale in production.

With the expansion of digital environments and increased data collection from user interactions, new forms of personalization emerged, relying on the tracking of user behavior across digital platforms. In this context, hyper-personalization is defined as personalization based on the integration of various sources of behavioral, contextual, and historical data, allowing content, offers, and interactions to be tailored according to observed consumer behavior in real time (Davenport, 2023; Jain et al., 2021; Micu et al., 2022; Pukas, 2022; Srivastav, 2025; Valdez Mendia & Flores-Cuautle, 2022).

Among the digital environments where these practices are implemented, e-commerce provides a relevant context for analyzing personalization strategies. E-commerce platforms track user interactions throughout the browsing experience, facilitating the observation of behavioral patterns and the adaptation of offers and recommendations based on these records (Raji et al., 2024; Nguyen et al., 2024).

Current hyper-personalization practices are thus understood as the evolution of analytical and behavioral routines in digital environments, particularly on e-commerce platforms that systematically track user interactions. Strategically, these routines can be interpreted as organizational processes for identifying and exploiting behavioral patterns in data-driven contexts.

2.2 E-COMMERCE AS A CONTEXT FOR APPLYING HYPERPERSONALIZATION

The growth of e-commerce has transformed consumer dynamics and the relationship between companies and customers (Raji et al., 2024). Initially associated with convenience and expanded access to consumption, e-commerce has evolved into a data-driven ecosystem where user experience and behavioral analysis drive competitive differentiation (Nandy & Kirit, 2025). Every click, view, or transaction generates digital traces that, when analyzed, enable the identification of navigation patterns and consumer behavior within e-commerce environments, as well as the inference of purchase intentions based on recorded interactions (Raphaeli et al., 2017; Sakar et al., 2018).

E-commerce thus serves as a testing ground for personalization practices by allowing the impact of various stimuli to be examined and measured in real time (Lemon & Verhoef, 2016; Wang, 2024). The customer journey is organized around multiple touchpoints such as searches, ads, recommendations, and social media interactions (Lemon & Verhoef, 2016), which capture and may influence consumer behavior (Pappas, 2018). Unlike physical interactions, digital journeys can be recorded and modeled in detail (Schweidel et al., 2022), supporting predictive analytics and automated interventions (Wang, 2024).

Among the behavioral data generated in this environment, clickstream data captures the sequence of user clicks and interactions (Wang et al., 2017). These records reflect consumer decisions throughout the online journey, including product views, additions to the shopping cart, and completed purchases, thereby providing a detailed representation of digital behavior (Aylin Tokuç & Dag, 2025; Liu et al., 2024; Thirumagal et al., 2024). Analysis of this data facilitates the identification of browsing patterns, the inference of purchase intentions, and the development of recommendation models (Montgomery et al., 2004), with recent studies reporting accuracy levels of 72–75% (Liu et al., 2024; Zhou & Hudin, 2024).

From a managerial perspective, clickstream data offers insights into consumer browsing, enabling organizations to extract behavioral insights and support data-driven strategic decisions in digital environments (Montgomery et al., 2004; Wedel & Kannan, 2016). These records also allow for tracking the customer lifecycle and tailoring content, communications, and marketing stimuli across the digital journey (Gomes & Meisen, 2023; Patnaik & Bhowmick, 2022).

2.3 PREDICTIVE MODELING AND CLICKSTREAM AS THE BASIS FOR MEASUREMENT

The digitization of consumer-platform interactions has broadened the use of behavioral data in analyzing consumption patterns. Such data enable the development of predictive models to identify browsing patterns and support organizational decision-making (Davenport, 2023; Wedel & Kannan, 2016). In e-commerce, predictive modeling relies on clickstream data, which records the sequence of user actions from initial access to conversion or cart abandonment (Bucklin & Sismeiro, 2009; Montgomery et al., 2004). These records include details such as time spent on pages, click sequences, products viewed, and transactions completed, facilitating observation of consumers' decision-making processes in digital environments (Liu et al., 2024; Mahajan et al., 2024).

Analyzing this data enables identification of behavioral patterns associated with product exploration, alternative evaluation, and purchasing decisions. Based on these patterns, statistical models and predictive algorithms can estimate the likelihood of purchase, navigation abandonment, or conversion along the digital journey (Liu et al., 2024; Zhou & Hudin, 2024). Clickstream data thus provide an empirical foundation for investigating how digital interactions can be translated into analytical insights to support personalization strategies on online platforms. By recording observable user behaviors, enabling the operationalization of behavioral indicators linked to consumer interactions in digital environments.

In this study, clickstream records are used as an empirical source to construct behavioral indicators that measure the construct under analysis. These data are used to identify navigation patterns that provide empirical evidence of the processes associated with personalization in data-driven digital environments.

2.4 FROM RESOURCE-BASED VIEW THEORY TO DYNAMIC CAPABILITIES THEORY

Resource-based view theory, grounded in Penrose (1959) and the seminal work of Wernerfelt (1984), posits that competitive advantage arises from the possession of valuable, rare, inimitable, and organized resources (Barney & Hesterly, 2007). In hyper-personalization, these resources are primarily intangible and technological, including data infrastructure, algorithms, proprietary databases, and analytical capabilities (Buiak et al., 2024; Dahake, Mohare & Somani, 2023; Hitt, Ireland & Hoskisson, 2017).

Nevertheless, the resource-based view, which assumes relatively stable environments, has shown limitations in explaining the sustainability of competitive advantage in settings marked by rapid technological change and globalization (Eisenhardt & Martin, 2000). In response to increasing turbulence, Teece, Pisano, and Shuen (1997) proposed the dynamic capabilities theory, offering a process-oriented and evolutionary perspective. Whereas the resource-based view explains what generates competitive advantage (resource possession), the dynamic capabilities theory addresses how that advantage is renewed (Teece, Pisano & Shuen, 1997).

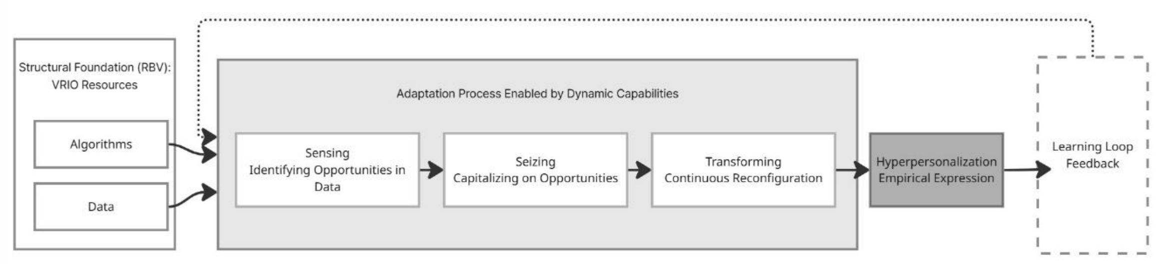
Teece (2007) later refined this theory by operationalizing it into three interrelated capabilities: sensing, which entails identifying opportunities and threats through systematic monitoring of trends, data, and behavioral patterns; seizing, which involves mobilizing resources and converting analytical insights into strategic decisions, innovations, or personalized experiences; and reconfiguring, which concerns redesigning and recombining assets, systems, and routines to ensure continuous alignment with competitive dynamics and enhance organizational adaptability. According to the author, the core of these capabilities is "maintaining evolutionary fitness as markets and technological opportunities change" (Teece, 2007).

From this perspective, hyper-personalization results not merely from the possession of data and algorithms (the resource-based view), but from the organization's dynamic capacity to learn from behavioral data (sensing), translate these insights into customized experiences (seizing), and continuously update its models and structures (reconfiguring).

The literature has further evolved toward the concept of dynamic digital capabilities (DDC), detailing the microfoundations essential for adaptation in digital environments (Albannai et al., 2024; Ellström et al., 2022; Warner & Wäger, 2019). DDC comprises three dimensions: digital detection (monitoring and interpreting data and emerging technologies), digital seizing (mobilizing resources and agile prototyping), and digital transformation (ongoing reconfiguration of processes, business models, and structures).

Hyper-personalization can therefore be interpreted as an organizational phenomenon dependent on the development of DDC that focuses on the interpretation and mobilization of behavioral data. The proposed framework (Figure 1) synthesizes this theoretical integration, positioning the analytical and behavioral infrastructure of hyper-personalization as the empirical expression of a strategic system.

Figure 1
The framework of hyper-personalization as a dynamic capability



The structural foundation, rooted in the resource-based view, provides essential strategic resources (e.g., algorithms and data) that may exhibit value, rarity, inimitability, and non-substitutability. These resources are mobilized through dynamic capabilities, in which the organization identifies opportunities from data (sensing), capitalizes on them by developing personalized offerings (seizing), and continuously reconfigures its resources and processes to sustain alignment with market changes (reconfiguring). This cycle is reinforced by the outcomes generated by data-driven personalization practices, forming a continuous learning loop. Consequently, hyper-personalization is approached in this study not as a directly observable phenomenon, but as an analytical outcome enabled by DDC in operation.

Hence, the behavioral and analytical infrastructure associated with hyper-personalization can be seen as an empirical manifestation of DDC, reflecting organizations' abilities to interpret and mobilize data and algorithms to create value, which requires integration among technological infrastructure, organizational learning, and ongoing strategic reconfiguration.

2.5 HYPOTHESES AND CONCEPTUAL FRAMEWORK OF THE HYPER-CONSTRUCT

Based on the literature, data generated through digital interactions can be interpreted as behavioral signals of consumer behavior in online environments. On e-commerce platforms, clickstream records provide insights into how consumers explore products, evaluate alternatives, and make decisions throughout the digital journey (Bucklin & Sismeiro, 2009; Montgomery et al., 2004). From a dynamic capabilities perspective, these signals inform organizational processes of sensing and seizing opportunities in digital environments (Teece, 2007). Navigation patterns can thus be treated as informational inputs in data-driven personalization practices.

In this study, the HIPER construct represents the informational potential inherent in browsing patterns observed in clickstream data. Therefore, the construct does not correspond directly to organizational hyper-personalization but rather to the behavioral signals that analytical systems can exploit within digital personalization processes.

Accordingly, the following hypotheses are proposed:

The intensity of product views indicates the volume of interaction with product stimuli during a session (Bucklin & Sismeiro, 2009; Montgomery et al., 2004).

H1. Higher intensity of product views per session is positively associated with hyper-personalization potential.

The diversity of products viewed reflects the breadth of interests explored during browsing (Bucklin & Sismeiro, 2009; Moe, 2003).

H2. Greater diversity of products viewed per session is positively associated with hyper-personalization potential.

The proportion of product views to total session events indicates the extent to which browsing focuses on product evaluation activities.

H3. A higher proportion of product views relative to total session events is positively associated with hyper-personalization potential.

Conversion signifies the transformation of attention into action and provides evidence of revealed preference (Lemon & Verhoef, 2016).

H4. A higher conversion rate per session is positively associated with hyper-personalization potential.

3 METHODOLOGICAL ASPECTS

This study adopts a quantitative, observational, and applied approach, utilizing secondary data derived from browsing and transaction events in an e-commerce environment. The methodological objective is to empirically operationalize hyperpersonalization potential based on observable behavioral patterns, thereby transforming a strategic, abstract, and not directly measurable phenomenon into a latent construct suitable for empirical estimation. For this, SEM was used as it can measure latent variables and simultaneously assess the relationships between the theoretical construct and its observable indicators. The choice of SEM is based on the premise that hyperpersonalization, as a system’s analytical and behavioral capacity, is not directly observable as a single variable. Its identification requires combining empirical manifestations of user navigation, product exploration, and the transformation of attention into higher-value actions, making an estimation of a reflective measurement model appropriate.

The empirical dataset comprises e-commerce navigation and transaction event logs, structured at the event level and containing the following variables: UserID, SessionID, Timestamp, EventType, ProductID, Amount, and Outcome. The analyzed dataset includes 74,817 records, corresponding to 1,000 users and 10,000 distinct UserID-SessionID pairs, covering interactions from January 1, 2024, to July 24, 2024. The observed events include, among others, *page_view*, *click*, *product_view*, *add_to_cart*, purchase, login, and logout.

The analytical unit of the study was the browsing session. Since the SessionID identifier is not globally unique in the dataset, sessions were defined by combining UserID and SessionID. This methodological decision prevents undue aggregations across distinct users and ensures greater consistency in behavioral tracking at the session level.

This dataset was selected for its relevance to the research problem. Because it contains explicit events related to browsing, product viewing, adding to cart, and purchasing, the database enables the derivation of behavioral indicators directly aligned with the empirical foundations of hyperpersonalization in a digital environment. In this context, the empirical environment serves as a proof-of-concept for measurement, aimed at operationalizing the behavioral microfoundations underlying advanced personalization.

3.2 CENTRAL CONSTRUCT AND DEFINITION OF VARIABLES

The central construct of this study is HIPER, defined as the degree to which users' navigation and response patterns exhibit behavioral traits consistent with advanced personalization. Theoretically, this construct is grounded in the microfoundations of dynamic capabilities, particularly in the processes of sensing and seizing. Sensing refers to the ability to capture, identify, and interpret signals from the environment, while seizing denotes the ability to transform such signals into higher-value actions.

Nonetheless, these foundations were not modeled as distinct latent factors. Empirically, the model was specified as unidimensional and reflective, based on the premise that different behavioral manifestations of digital navigation serve as indicators of a single latent factor associated with the potential for hyperpersonalization. Thus, "sensing" and "seizing" serve as conceptual foundations for selecting indicators, rather than as latent dimensions estimated separately.

Variables were constructed at the session level by aggregating events based on UserID and SessionID. The HIPER construct was operationalized using four observed indicators. The first indicator, *n_product_view_session*, corresponds to the number of *product_view* events in each session and represents the intensity of behavioral exploration. The second, *n_unique_products_session*, is the number of distinct products viewed within product_view events and reflects the breadth of this exploration. The third, *ratio_product_view*, was calculated as the proportion of *product_view* events to the total number of events in the session, serving as a measure of the navigation's focus on product stimuli. The fourth metric, *conversion_rate_session*, was calculated as the ratio of the number of distinct products added to the cart to the number of product views in the session, and is interpreted as evidence of the effectiveness in converting attention into higher-value actions.

In the script, the *add_to_cart* event was identified by performing a textual search for the term "*cart*" in the labels of the EventType variable. To avoid division-by-zero errors, sessions without any product views were assigned a *conversion_rate_session* value of 0. Similarly, in sessions without *product_view*, the *n_unique_products_session* indicator was set to zero. Formally, the measurement model was specified as:

HIPER=~ *n_product_view_session+n_unique_products_session+ratio_product_view+conversion_rate_session*

Substantively, *n_product_view_session* and *n_unique_products_session* approximate the *sensing* component, as they reflect the intensity and diversity of exploration. In turn, *ratio_product_view* and *conversion_rate_session* approximate, respectively, the behavioral focus of the session and the ability to convert interest into action, thus providing an empirical basis for the seizing component.

3.3 PREPROCESSING AND ANALYSIS PROCEDURES

Data processing was conducted in Python. The *ecommerce_clickstream_transactions.csv* file was imported using *pandas.read_csv()*, and metrics were constructed by aggregating the records at the session level. To reduce behavioral noise, sessions consisting of a single event were excluded (Bucklin & Sismeiro, 2009). Variables were normalized using z-scores to mitigate the effects of outliers and facilitate comparisons of factor loadings, in accordance with Hair et al. (2019). Extreme outliers, detected using the interquartile range method, were evaluated and removed when attributed to systemic logging errors (Tukey, 1977).

The variables "Amount" and "Outcome," although present in the dataset, were not used directly in measuring the HIPER construct in this specification. Similarly, the "Timestamp" variable was retained as event metadata without being directly included in the final reflective model, as the unit of analysis was the session identified by the *UserID-SessionID* pair.

Statistical analysis was conducted using a single-factor reflective SEM, estimated in Python with the semopy library. In the script, the model specification was defined using measurement syntax, followed by fitting with *Model.fit(panel)* and inspecting the parameters with *model.inspect()*. By default, the library uses the MLW objective function and the SLSQP solver, and it provides global fit statistics via the *calc_stats()* routine.

Assessment of measurement quality was structured along four dimensions. First, the factorability of the correlation matrix was examined using the Kaiser-Meyer-Olkin index and Bartlett's test of sphericity. The Kaiser-Meyer-Olkin index served as a preliminary diagnostic of sample adequacy, while Bartlett's test assessed whether the correlation matrix significantly differs from an identity matrix. Overall Kaiser-Meyer-Olkin values greater than 0.60 and statistical significance in Bartlett's test were used as operational benchmarks.

The second phase involved evaluation of the measurement model. Factor loadings were examined for sign, magnitude, and statistical significance, with values above 0.50 used as a criterion, and a preference for loadings above 0.70. The construct's internal consistency was assessed using composite reliability, with a minimum threshold of 0.70. When reported, average extracted variance was interpreted as evidence of convergent validity if it exceeded the 0.50 threshold.

The third aspect addressed the overall fit of the model using statistics such as the chi-square test, comparative fit index, Tucker-Lewis index, root mean square error of approximation, and standardized root mean square residual. For interpretation, operational reference points were set at comparative fit index and Tucker-Lewis index values of 0.90 or higher, and at root mean square error of approximation and standardized root mean square residual values of 0.08 or lower. These cutoff points were treated as guidelines for evaluation rather than strict acceptance rules.

The fourth area focused on the substantive interpretation of the estimated parameters. The statistical significance of the loadings was not considered in isolation as evidence of substantive robustness. Given that some indicators derive from a similar operational basis, particularly the *product_view* events, interpretive analysis also considered the heterogeneity of magnitudes, the possibility of informational redundancy among measures, and the theoretical coherence between the indicator and the construct.

4. ANALYSIS OF RESULTS

4.1 CHARACTERIZATION OF THE ANALYTICAL SAMPLE

The analyzed dataset comprises 74,817 event records, aggregated into 10,000 browsing sessions from 1,000 users. In accordance with the adopted methodological strategy, the analytical unit was the session, operationalized as the combination of *UserID* and *SessionID*. Based on this aggregation, four observed indicators of the HIPER construct were developed: *n_product_view_session*, *n_unique_products_session*, *ratio_product_view*, and *conversion_rate_session*.

This structure facilitates the capture of diverse behavioral manifestations in digital navigation. Whereas *n_product_view_session* and *n_unique_products_session* represent, respectively, the intensity and breadth of product exploration within a session, *ratio_product_view* captures the relative focus of navigation on product stimuli, and *conversion_rate_session* reflects the effectiveness of converting attention into higher-value actions, operationalized in this study as items added to the cart. In this configuration, the estimated model was designed to verify whether these indicators empirically converge on a single latent factor, interpreted as hyper-personalization potential.

4.2 RESULTS OF THE MEASUREMENT MODEL

Estimation of the single-factor reflective model indicated that all indicators were positively and statistically significantly associated with the latent construct HIPER (Table 1).

Table 1
Estimated parameters of the HIPER construct measurement model

lval	**op**	**rval**	**Estimate**	**Std. Error**	**z-value**	***p*-value**
n_product_view_session	~	HIPER	1	-	-	-
n_unique_products_session	~	HIPER	1.0150	0.0007	1,523.25	0
ratio_product_view	~	HIPER	0.1334	0.0009	141.57	0
conversion_rate_session	~	HIPER	0.1205	0.0077	15.61	0
HIPER	~~	HIPER	1.0382	0.0147	70.57	0
conversion_rate_session	~~	conversion_rate_session	0.6184	0.0087	70.71	0
n_product_view_session	~~	n_product_view_session	0.0017	0.0004	4.2674	1,98E-05
n_unique_products_session	~~	n_unique_products_session	0.0014	0.0004	3.3907	6,97E-04
ratio_product_view	~~	ratio_product_view	0.0092	0.0001	70.61	0

The *n_product_view_session* indicator served as the reference for factor scaling, with a fixed loading of 1. Among the indicators, *n_unique_products_session* exhibited the highest factor loading (1.01), with a standard error of 0.00, a z-statistic of 1,523.25, and a *p*-value below 0.001. The high magnitude of the loadings reinforces that the intensity and diversity of sensing are central to Hyper-Personalization Potential, indicating that users exposed to a broader range of products engage more substantially with the construct's fundamental aspects, consistent with the algorithmic personalization literature (Micu et al., 2022).

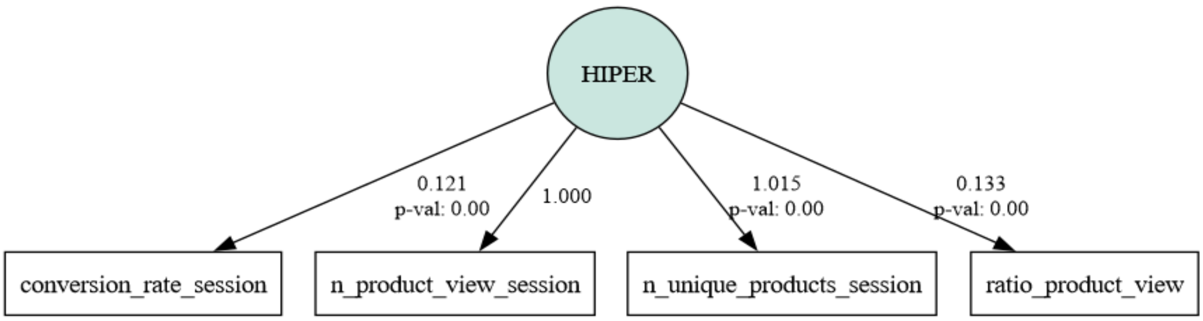
The indicator *ratio_product_view* had a loading of 0.13, a standard error of 0.00, a z-statistic of 141.57, and a *p*-value below 0.001. *Conversion_rate_session* showed a factor loading of 0.12, a standard error of 0.00, a z-statistic of 15.61, and a *p*-value below 0.001. This pattern is theoretically consistent, demonstrating the complementary yet distinct roles of these indicators in measuring the HIPER construct. The former (*ratio_product_view*) improves sensing quality, while the latter (*conversion_rate_session*) empirically captures behavioral aspects of seizing, which is conceptualized as the transformation of interest into higher-value actions throughout the digital journey.

The significance and positive direction of all factor loadings support convergence toward the HIPER construct, in accordance with the criteria established by Hair et al. (2019). Nonetheless, the differing magnitudes of the loadings necessitate careful, nuanced interpretation.

4.3 HETEROGENEITY OF FACTOR LOADINGS AND SUBSTANTIVE INTERPRETATION

To complement the statistical interpretation, Figure 2 presents the path diagram of the fitted model. This diagram visually summarizes the relational structure between HIPER and its behavioral indicators, organized according to their theoretical relevance to the processes of sensing and seizing.

Figure 2
Path diagram of the HIPER construct measurement model



In the diagram, arrows originate from the latent HIPER factor and converge on each indicator, illustrating the model's reflective nature. The coefficients on the arrows represent standardized factor loadings, providing a statistical measure of the strength of association between the factor and each indicator. All loadings are positive and significant (*p*-value = 0.00), mirroring the tabular results.

The distribution of factor loadings indicates that the HIPER construct, as operationalized here, is more strongly represented by indicators related to product exploration than those connected to session focus and conversion. This is clear in the contrast between the high loading for *n_unique_products_session* and the considerably lower loadings for *ratio_product_view* and *conversion_rate_session*.

Analytically, this pattern suggests that the primary empirical dimension of the construct is concentrated in users' exploratory behaviors, particularly in the diversity of products viewed per session. Thus, the proposed latent measure reflects most strongly the "sensing" component, which is related to exploration, monitoring, and extending engagement with product stimuli. In contrast, indicators more closely tied to the seizing component, especially *conversion_rate_session*, despite significant differences, showed weaker associations with the common factor.

This finding aligns with our theoretical framework; hyper-personalization primarily depends on the ability to capture and organize user behavioral signals. Simultaneously, it shows that empirical operationalization emphasizes the exploratory aspect of navigation more than decision-making or conversion.

4.4 STATISTICAL PRECISION AND INTERPRETATIVE CAUTIONS

The observed z-scores, particularly for *n_unique_products_session* and *ratio_product_view*, are exceptionally high. While this underscores the statistical significance of the parameters, such magnitudes should not be interpreted as definitive evidence of greater substantive robustness. As some indicators are derived from closely related operational bases (specifically *product_view* events), a considerable degree of statistical regularity between measures may exist, leading to smaller standard errors and inflated z-statistics.

Therefore, the empirical findings should be interpreted cautiously. The model provides evidence of a consistent statistical association between the indicators and the HIPER construct, but this does not exclude the possibility of informational overlap among variables stemming from a shared behavioral core. Rather than implying full and definitive validity, these results should be considered initial evidence supporting the construct's measurement, which remains open to future refinement.

4.5 ESTIMATED VARIANCES AND MEASUREMENT QUALITY

Regarding the estimated variances, the latent HIPER factor variance was positive and statistically significant, indicating adequate construct variability across the analyzed sessions. The residual variances of the indicators were also positive and significant, suggesting that, while the common factor explains a substantial portion of the covariance among measures, a non-negligible residual component persists in each indicator.

Specifically, *conversion_rate_session* exhibited a residual variance of 0.61, indicating that much of its variability is not explained by the common latent factor. This finding corresponds with the nature of this indicator, which is more sensitive to contextual and behavioral aspects of sessions. *Ratio_product_view* showed a residual variance of 0.00, whereas *n_product_view_session* and *n_unique_products_session* exhibited smaller, yet statistically significant, residual variances. Collectively, these results reinforce the interpretation that the model captures a reasonable common factor but does not fully account for the complexity of observed behaviors.

4.6 SUMMARY OF THE FINDINGS

Overall, the results support the premise that observable patterns of navigation and interaction in an e-commerce environment can be used to empirically measure the potential for hyper-personalization. The statistical convergence among the four indicators and the latent HIPER factor suggests initial empirical support for the construct, particularly when operationalized via measures of product exploration at the session level.

At the same time, variation in factor loadings indicates that indicators contribute unevenly to the empirical composition of the common factor. Therefore, the model should be interpreted as a proof-of-concept measurement, rather than a definitive, exhaustive account of the phenomenon. This conclusion is important as it preserves the study's central contribution (i.e., transforming an abstract strategic concept into an empirically observable construct) without overstating the scope of the results

5 DISCUSSIONS OF RESULTS

The results indicated that browsing patterns recorded in clickstream data can be used to empirically operationalize behavioral dimensions associated with data-driven personalization in digital environments. The statistical convergence between the observed indicators and the latent HIPER construct suggests that metrics derived from digital interactions capture behavioral signals reflecting how users explore information and respond to product stimuli throughout the purchase journey. These findings align with studies highlighting the potential of clickstream data to enhance understanding of consumer decision-making processes in online contexts (Micu et al., 2022; Kaptein & Eckles, 2012).

Indicators related to the intensity and diversity of product views showed the strongest associations with the latent construct. This result indicates that product exploration constitutes a predominant dimension of the behavioral patterns captured by the model. Analytically, this behavior can be interpreted as a sign of increased exposure to different product stimuli during a user's browsing session. In the digital marketing literature, this behavior has been associated with the exploratory phase of the consumer journey, in which different alternatives are evaluated before decision-making (Bucklin & Sismeiro, 2009; Moe, 2003).

The predominance of these indicators is also consistent with the perspective of dynamic capabilities. In Teece's (2007) framework, the sensing process involves identifying and interpreting signals from the environment. In digital contexts, these signals may arise from interactions recorded on online platforms, where browsing patterns reveal consumers' preferences, interests, and search trajectories.

Thus, the intensity and diversity of product views can be interpreted as behavioral manifestations of the generation of information for analytical processes. Indicators associated with browsing focus and conversion also showed a positive association with the construct, although to a lesser extent than exploration metrics. This pattern suggests that, while exploratory behavior has the highest factor loading in the model, the transformation of attention into action is also captured by the model. The literature on the customer journey highlights that conversion occurs later in the decision-making process, when interactions accumulated throughout navigation may translate into behaviors associated with purchase decisions, such as adding products to the cart or making a purchase (Lemon & Verhoef, 2016).

The heterogeneity of the factor loadings indicates that different behavioral manifestations contribute differently to the measurement of the HIPER construct. Exploration indicators capture the informational dimension of navigation more strongly, while focus and conversion indicators reflect later stages of the decision-making process. This pattern suggests that the construct is more strongly associated with the exploratory phase of user interaction, while still incorporating elements related to navigation effectiveness.

From a methodological standpoint, the results reinforce the utility of SEM for operationalizing latent constructs derived from digital behavioral data. The single-factor reflective model enabled the integration of diverse observable manifestations of navigation into a common analytical framework, consistent with approaches that use observable indicators to measure latent phenomena in organizational and marketing research (Diamantopoulos & Siguaw, 2006; Fornell & Larcker, 1981).

In theoretical terms, the findings bring the literature on digital personalization closer to the perspective of dynamic capabilities by suggesting that interaction patterns recorded in digital environments can be interpreted as relevant sources of information for understanding data-driven organizational processes.

6 FINAL CONSIDERATIONS

The objective of this study was to propose and test an empirical model to measure hyper-personalization potential (HIPER) in e-commerce environments. To this end, a single-factor reflective structural equation model was estimated and applied to behavioral indicators derived from clickstream data, including viewing intensity, product diversity, proportion of views, and conversion rate.

The results indicate that browsing patterns recorded in clickstream data can serve as empirical indicators of the informational potential associated with hyperpersonalization in digital environments. Indicators of the intensity and diversity of product exploration showed a stronger association with the latent construct, while metrics of browsing focus and conversion contributed in complementary ways to its measurement.

From an organizational strategy perspective, the results suggest that behavioral patterns observed in digital environments can serve as signals for sensing and seizing processes described in the dynamic capabilities literature (Eisenhardt & Martin, 2000; Teece, 2007). In this sense, the study links behavioral data derived from digital interactions to the literature on dynamic capabilities and data-driven personalization.

From a theoretical perspective, this study contributes by linking behavioral data to the theory of dynamic capabilities. From a methodological perspective, it demonstrates the use of clickstream data as an empirical basis for constructing indicators of a latent construct derived from behavioral patterns observed in digital environments.

The study has limitations related to the availability and level of detail of the clickstream data used, as well as the restriction that the analysis was conducted within a single e-commerce environment, which limits the generalizability of the findings. Future research could extend the analysis by including contextual variables, post-conversion engagement metrics, and loyalty indicators, and by testing the model across different platforms and segments.

Another issue concerns the effects of algorithmic curation on interaction patterns observed on digital platforms. Despite not measured in this study, recommendation systems can influence exposure to content and products, raising questions about consumer autonomy and the diversity of choice (Shin, Rasul & Fotiadis, 2022). Future research may also explore ethical and regulatory aspects of data-driven personalization, including data governance, algorithmic transparency, and privacy.

Lastly, clickstream data allow one to observe interaction patterns that serve as signals for sensing and seizing processes, contributing to an understanding of the potential of hyper-personalization in data-driven digital environments.

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