THE IMPACT OF PERSONALIZATION ON CONTINUANCE INTENTION TO USE E-COMMERCE PLATFORMS: THE MEDIATING ROLE OF PERCEIVED USEFULNESS AND PERCEIVED ENJOYMENT

TÁC ĐỘNG CỦA CÁ NHÂN HÓA ĐẾN Ý ĐỊNH TIẾP TỤC SỬ DỤNG NỀN TẢNG THƯƠNG MẠI ĐIỆN TỬ: VAI TRÒ TRUNG GIAN CỦA CẢM NHẬN HỮU ÍCH VÀ CẢM NHẬN THÍCH THÚ

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Abstract - This study examines the effect of perceived personalization (CNH) on continuance intention to use (YD) e-commerce platforms through the mediating roles of perceived usefulness (HI) and perceived enjoyment (TT). Data from 384 Vietnamese users with at least six months of experience using e-commerce platforms were analyzed using PLS-SEM combined with fsQCA. The PLS-SEM results confirm that CNH exerts both a direct effect and an indirect effect on YD by increasing users' HI and TT. The fsQCA findings show that there is no single decisive factor, and they clarify how different configurations of conditions lead to the target behavior. The configuration combining CNH with HI achieves the highest explanatory power; additionally, HI emerges as a core condition that can offset functional limitations to sustain YD.

Key words - Perceived personalization; Perceived usefulness; Perceived enjoyment; Continuance intention; E-commerce; fsQCA

Tóm tắt - Nghiên cứu xem xét tác động của Cảm nhận cá nhân hóa (CNH) đến Ý định tiếp tục sử dụng (YD) trên các nền tảng Thương mại điện tử (TMĐT) thông qua cơ chế trung gian của Cảm nhận hữu ích (HI) và Cảm nhận thích thú (TT). Dữ liệu thu thập từ 384 người dùng tại Việt Nam có tối thiểu 06 tháng kinh nghiệm sử dụng nền tảng TMĐT, được phân tích bằng phương pháp PLS-SEM kết hợp fsQCA. Phân tích PLS-SEM khẳng định CNH không chỉ tác động trực tiếp mà còn gián tiếp thúc đẩy YD thông qua việc nâng cao mức độ HI và TT của người dùng. Phân tích fsQCA chỉ ra rằng không tồn tại yếu tố đơn lẻ mang tính quyết định, đồng thời làm rõ sự tương tác giữa các nhóm điều kiện dẫn đến hành vi. Nhóm điều kiện CNH kết hợp với HI đạt giá trị giải thích đặc thù cao nhất, ngoài ra, HI được xác định là yếu tố quan trọng trong các nhóm điều kiện, đóng vai trò bù đắp cho các hạn chế về mặt chức năng nhằm duy trì YD.

Từ khóa - Cảm nhận cá nhân hóa; Cảm nhận hữu ích; Cảm nhận thích thú; Ý định tiếp tục sử dụng; Thương mại điện tử; fsQCA

1. Research overview

With the market projected to reach USD 181 billion in 2025, Southeast Asia's e-commerce market has affirmed its pivotal role in the digital economy [1]. To meet consumers' increasingly diverse and complex needs, personalization has become a dominant trend [2]. In this context, perceived personalization (CNH) - the extent to which users perceive that information has been personalized specifically for them [3] - has been shown to be a key determinant of users' behavioral outcomes and post-use responses, particularly continuance intention to use (YD) [4], [5]. Theoretically, the value of CNH in recommender systems is generated by the combination of information-processing effectiveness (HI) and users' interactive experience (TT) [6] - [8]. However, implementing CNH in recommender systems poses a critical managerial challenge regarding resource allocation, requiring operators to weigh whether to prioritize algorithms to optimize usefulness (HI) or to invest in interface and content experiences to increase users' enjoyment (TT) [9]. Although CNH has been conceptualized and measured as a latent perceptual construct and has been demonstrated to positively affect customer satisfaction [5], [4], [10] - [13], two research gaps remain.

First, although the effects of HI and TT have been established as two important mediators leading to behavioral outcomes [6], [8], [14], [15], most prior studies have primarily focused on initial adoption (use intention, acceptance intention, etc.). Moreover, TT has mainly been found to influence YD indirectly through satisfaction as a mediator, and studies that model and simultaneously test the direct effects of these two factors on YD remain limited [16]. This results in a less systematic understanding of the roles of cognitive and affective dimensions in sustaining loyalty. Accordingly, this study tests the dual mediation effects of HI and TT to clarify the mechanism through which CNH influences YD, thereby providing scientific evidence to help firms identify strategic priorities for maintaining user loyalty.

Second, existing research has largely relied on the assumption of linear relationships [17] - [20]. In contrast, user behavior is inherently complex, and examining the isolated effect of each factor cannot explain how factors combine to produce behavioral outcomes [21], [22]. As a result, managerial recommendations are often generalized and lack sufficient depth to address real-world resource-allocation problems. Therefore, this study integrates PLS-SEM and fsQCA to identify different configurations of CNH, HI, and TT that lead to YD, enabling managers to optimize resource allocation between functional (HI) and affective (TT) factors in order to maximize user retention effectiveness.

2. Theoretical background, hypotheses, and research model

2.1. Theoretical background and key concepts

2.1.1. Perceived personalization (CNH)

In the context of digital platforms, CNH is defined as the extent to which users perceive that recommendations are tailored to their preferences, interests, and personal needs [23]. In the early stage, Palmer [24] defined this concept based on technological capability to customize content and interfaces using behavioral data. Building on this foundation while shifting the focus toward cognitive psychology, Komiak and Benbasat [25] described it as the extent to which customers believe that the system truly understands and serves their distinct needs. Subsequent research further developed this concept by clearly distinguishing between actual personalization and perceived personalization, asserting that technical efforts are meaningless if customers do not perceive the fit of the system's personalized recommendations [5]. Accordingly, in this study, CNH is defined as customers' subjective belief that recommendations are designed specifically for them - when the system understands their needs, provides content aligned with their current preferences, and creates a sense of being cared for as an individual.

2.1.2. Extended Technology Acceptance Model (TAM)

The TAM theory, proposed by Davis [46], is a classic theoretical framework for explaining individuals' acceptance or rejection of technology based on two core factors: HI and perceived ease of use. By 1992, Davis and colleagues extended this model (e-TAM) by incorporating TT [27]. In the context of today's personalized recommender systems, as users have become relatively familiar with technology, usage effort is no longer a decisive barrier [28], [29]. Instead, utilitarian value (via HI) and experiential value (via TT) become two key mediating mechanisms linking personalization stimuli (Stimuli) to behavioral intention. Supporting this argument, empirical studies indicate that user experience in recommender systems is mainly shaped by content quality, content relevance, and enjoyment in interaction, rather than basic technical operations [8], [29] - [31]. Moreover, the influence of perceived ease of use tends to diminish over time or affects outcomes only indirectly through HI or satisfaction when user interfaces have become widespread and accessible [32], [33]. Therefore, this study applies e-TAM, focusing on the two mediators HI and TT to optimize explanatory power for recommender systems.

2.1.3. Stimulus–Organism–Response (SOR) theory

SOR theory [34], [35] posits that external stimuli (stimulus) affect individuals' internal psycho-physiological states (organism), thereby shaping corresponding behavioral responses (response). SOR has demonstrated broad applicability in research on consumer behavior in digital environments and e-commerce, particularly regarding personalization cues, content experience, and online interaction [36], [37], [38]; [39]. At the same time, SOR elucidates the causal relationship between environmental stimuli and behavioral responses through intermediate psychological and cognitive states, thereby influencing users' decisions to continue using or to avoid use [40] - [42]. In this study, CNH reflects an external characteristic of the recommender system (a stimulus from the technological environment), whereas HI (a cognitive state concerning functional benefits) and TT (a positive affective state) belong to users' internal processing layer and are thus classified as the Organism component; YD is identified as the Response.

2.2. Hypotheses and research model

2.2.1. Relationships among CNH, HI, and YD

In E-commerce context, YD is users' subjective desire to continue using an online platform in the future after prior experience, rather than returning to traditional (offline) channels or switching to another platform [43]. In the context of intense competition and rising costs of acquiring new customers, this study focuses on YD because it directly reflects customer retention effectiveness and the sustainability of e-commerce business models, which depend more on repeat purchasing behavior than on initial adoption alone [43] - [45].

HI is an extrinsic motivation reflecting an individual's belief that using a particular system will enhance performance and work outcomes [46]. In recent research, HI continues to be affirmed as one of the important determinants of intention to use and to continue using technology [47].

This study applies the SOR framework to explain user behavioral mechanisms on e-commerce platforms. In this model, CNH functions as a stimulus (by providing content, products, and services suited to each customer's specific needs). This compatibility significantly reduces information-search effort and cognitive costs, thereby directly enhancing perceptions of the platform's usefulness [48]. According to Bleier and Eisenbeiss [49], when recommendations become highly relevant to personal preferences, users will place greater value on what the system provides. Similarly, Aguirre et al. [50] argue that personalization features optimize the decision-making process, leading to increased HI in the e-commerce environment. Recent studies also indicate that receiving accurate, contextually relevant product recommendations makes users perceive the platform as more effective in meeting their shopping goals [51], [52]. Therefore, the following hypothesis is proposed:

H1: CNH positively affects HI.

According to TAM, HI is a strong predictor of behavioral intention. Users tend to continue using a ecommerce platform if they perceive that the system delivers practical benefits and high instrumental value [46].

Studies show that when users feel an application or platform helps them complete shopping more quickly and efficiently, their YD increases significantly [47], [53]. HI helps reduce psychological barriers and enhance perceived value, thereby promoting loyalty and sustainable usage behavior [54]. Therefore, this study proposes:

H2: HI positively affects YD.

According to SOR, CNH serves as a stimulus (Stimulus) that influences users' internal cognitive state, namely HI (Organism), which then leads to the final response of intention to continue using the platform (Response) [48], [55]. Integrating SOR and TAM helps clarify how personalized experiences are translated into practical value in users' perceptions, rather than being merely technical features [47], [53].

Accordingly, HI plays an important mediating role because personalization does not directly lead to long-term attachment; rather, it operates by increasing users' perceptions of the system's usefulness and effectiveness in addressing their personal needs [48]. Studies by Hu et al. [55] and Song et al. [53] also indicate that the effects of personalization features on user behavior mainly operate through the mechanism of enhancing perceived usefulness. Thus, HI is a key factor that transforms stimuli from the platform into customers' sustained engagement behavior [52]. Therefore, this study proposes the hypothesis:

H3: HI positively mediates the relationship between CNH and YD.

2.2.2. Relationships among CNH, TT, and YD

TT refers to the degree of fun and attractiveness users obtain during technology use [56]. Under TAM, TT represents an intrinsic motivation reflecting an individual's inherent pleasure, independent of performance-related outcomes [27]. In the e-commerce domain, this concept captures emotional gratification and hedonic value arising directly from the interaction process, beyond typical functional utilities [57]. According to Rahman et al. [58], providing personalized interactions fosters a sense of being understood and reduces cognitive strain, thereby creating psychological comfort. In addition, product customization features and flexible responses to individualized needs not only serve shopping purposes but also make the process more vivid and interesting [57]. When recommender systems present content aligned with personal preferences, users experience an exciting sense of discovery, increasing emotional attachment to the platform. Therefore, this study proposes:

H4: CNH positively affects TT.

TAM complements SOR by indicating that TT is an important factor determining users' attitudes and behavioral responses. Although Pereira and Tam [56] indicate that enjoyment influences YD largely through satisfaction, TT remains a core foundation for promoting sustainable shopping behavior [59]. Supporting this argument, Patel et al. [60] also suggest that TT, even with a small effect, still contributes to increasing purchase intention via online applications. From a motivational perspective, when individuals achieve emotional gratification during interaction, barriers related to cognitive effort are reduced, thereby strengthening the tendency to continue using the system in the long term [61]. Therefore, the following hypothesis is proposed:

H5: TT positively affects YD.

From the perspective of SOR theory, stimuli from the external environment can influence individuals' internal psychological states, thereby shaping specific behavioral responses [34]. In this study, CNH is regarded as the stimulus (Stimulus) that generates TT in users (Organism), thereby promoting YD (Response).

Numerous studies have reinforced the mediating role of TT in the relationship between systems and user behavior. Hu et al. [62] demonstrate that TT mediates the relationship between functional factors and repurchase intention, while Cuong [63] indicates that positive emotions such as TT mediate the relationship between CNH and YD on online shopping platforms. Similarly, Hateftabar [64] emphasizes that the enjoyment individuals experience during technology use, regardless of performance issues, still affects the extent of their engagement to the system. Therefore, the following hypothesis is proposed:

H6: TT positively mediates the relationship between CNH and YD.

2.2.3. Relationship between CNH and YD

Perceived personalization in e-commerce recommender systems plays an important role in promoting users' intention to continue using the platform. When customers perceive that recommended content, products, or services are based on their personal preferences and needs, they tend to value the relevance and usefulness of the recommendations more highly, thereby increasing satisfaction and commitment to the platform [17]. In addition, under the e-TAM model [27], personalization increases HI and TT, thereby enhancing perceived value and user trust and contributing to long-term usage intention [65], [55], [66]. In parallel, the SOR model [34], [35] explains that personalization, as a stimulus, positively affects users' psychological states (such as perceived fit and satisfaction), leading to the positive response of YD [67], [68]. Therefore, this study proposes:

H7: CNH positively affects YD.

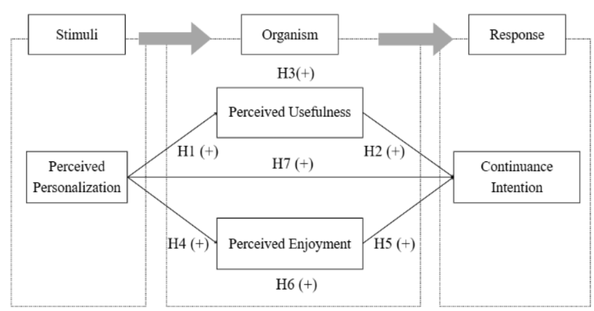

Figure 1. *Proposed Research Hypothesis Model*

Source: Compiled by the authors

3. Research methodology

3.1. Scale selection and questionnaire design

The measurement scales in the questionnaire were constructed using a five-point Likert format ranging from 1 to 5 to measure the relationships among CNH, HI, TT, and YD.

Specifically, CNH was measured using four observed items adopted from An et al. [23]. Next, HI was adopted from Liang et al. [69] with three observed items; TT was measured using five observed items adapted from Ashraf et al. [70]; and YD was measured using three observed items adapted from Bianchi and Saleh [71].

In addition, to support sample screening and profiling, the questionnaire collected basic demographic information including gender, age, and the duration and frequency of using e-commerce platforms.

3.2. Sampling and data collection

This study used a quantitative design with cross-sectional data, meaning that data were collected at a single point in time without tracking changes over time, through an online survey administered during 01/11/2025–01/01/2026. Respondents were users aged 18 to 45 in Vietnam, with at least six months of experience using e-commerce platforms such as Shopee, Lazada, Tiki, and TikTokShop. A convenience sampling approach was employed, and the questionnaire was distributed via email, social media, and internal communication channels. The survey process ensured voluntariness, anonymity, and confidentiality to comply with research ethics.

A total of 407 responses were obtained, of which 384 were valid after screening, meeting the sample-size requirement for SEM analysis with 15 observed variables [72].

3.3. Data analysis methods

This study combined PLS-SEM and fsQCA to optimize the ability to explain complex social phenomena. To test the proposed model, descriptive statistics and scale reliability assessments were conducted in SmartPLS 4.0 to evaluate the measurement model and the research hypotheses. Next, fsQCA was added to identify diverse configurations of conditions affecting YD, rather than examining isolated net effects [73].

Following the three-stage procedure suggested by Ragin [74] and Kraus et al. [75], the analysis included: (1) calibration, using the technique proposed by Marx et al. [76], to transform Likert-scale values into fuzzy-set scores ranging from 0.00 to 1.00 based on three qualitative anchors following Pappas and Woodside [77]: 0.95 (full membership), 0.50 (crossover point), and 0.05 (full non-membership); (2) analysis of necessary conditions and construction of the truth table; and (3) Boolean minimization to obtain the intermediate solutions, assessed via consistency and coverage indices. This combination enables generalizability from SEM and contextual precision from fsQCA, particularly when a condition can be sufficient but not unique in producing an outcome [75], [78].

4. Research findings

4.1. Sample description

The sample profile in Table 1 indicates a relatively balanced gender distribution, with 48.70% male and 51.30% female respondents. Regarding age, the 18–35 group accounts for over 72% of the sample, in which the 18–25 subgroup represents 42.71%. In terms of usage duration, most participants show stable engagement: 81.21% have used e-commerce platforms for more than one year, including 37.24% with over three years of experience. Regarding usage frequency, respondents using e-commerce platforms a few times per week constitute the largest group (38.02%), followed by weekly and monthly users. Overall, the sample reflects experienced users with high engagement and diverse usage patterns, thereby supporting the representativeness and reliability of the dataset for analyzing consumer behavior on digital platforms.

Table 1. *Demographic profile of the respondents*

Characteristics		Frequency	Percentage (%)
Gender	Male	187	48.70
	Female	197	51.30
Age group	18 - 25 years old	164	42.71
	26 - 35 years old	113	29.43
	36 - 45 years old	107	27.86
Usage time	6 - 12 months	76	19.79
	1 - 3 months	165	43.97
	Over 3 years	143	37.24
Usage frequency	Daily	58	15.10
	Several times per week	146	38.02
	Once per week	80	20.83
	Several times per month	74	19.27
	Less than once per month	26	6.77
Total		886	100

Source: Compiled by the authors

4.2. Measurement model assessment

Table 2. *Outer loadings, Cronbach's Alpha, Composite reliability, Average Variance Extracted (AVE)*

Variable	Observed variables	Outer Loading	Cronbach's alpha	Composite Reliability	AVE
CNH	CNH1	0.831	0.885	0.921	0.744
	CNH2	0.877			
	CNH3	0.852			
	CNH4	0.889			
HI	HI1	0.849	0.84	0.903	0.757
	HI2	0.867			
	HI3	0.895			
TT	TT1	0.783	0.868	0.905	0.655
	TT2	0.8			
	TT3	0.865			
	TT4	0.801			
	TT5	0.797			
YD	YD1	0.861	0.856	0.912	0.776
	YD2	0.892			
	YD3	0.889			

Source: Compiled by the authors

Results in Table 2 show that all outer loadings for CNH, HI, TT, and YD range from 0.783 to 0.895, exceeding the recommended threshold of 0.708, indicating substantial contributions of observed indicators to the variance of their corresponding latent constructs [79]. In addition, internal consistency reliability indicators - including Cronbach's alpha and composite reliability (CR) - are all above the acceptable thresholds suggested by Henseler et al. [80], confirming good internal consistency and reliability for subsequent analyses. Moreover, the AVE values range from 0.655 to 0.776, surpassing the 0.50 criterion proposed by Fornell and Larcker [81], indicating that the latent constructs explain, on average, over 65% of the variance in their indicators and thus establishing convergent validity for the research model.

Discriminant validity, assessed using HTMT (Table 3), shows that all values range from 0.271 to 0.688, below the recommended threshold of 0.85 [82]. This confirms satisfactory discriminant validity, ensuring construct distinctiveness and supporting further structural analysis.

Table 3. *Heterotrait - Monotrait (HTMT)*

	YD	TT	CNH
TT	0.478		
CNH	0.567	0.370	
HI	0.688	0.271	0.583

Source: Compiled by the authors

4.3. Structural model assessment and hypothesis testing

Table 4. *Path coefficient value*

Hypothesis	Relationships	Path coefficient (β)	P-Values	Result
H1	CNH → HI	0.502	0.000	Supported
H2	HI → YD	0.428	0.000	Supported
H3	CNH → HI → YD	0.215	0.000	Supported
H4	CNH → TT	0.327	0.000	Supported
H5	TT → YD	0.251	0.000	Supported
H6	CNH → TT → YD	0.082	0.000	Supported
H7	CNH → YD	0.198	0.000	Supported

Source: Compiled by the authors

Bootstrapping with 5.000 resamples was used to test the statistical significance of path coefficients in the model. Table 4 indicates that all seven hypotheses (H1–H7) are supported at $P < 0.05$, thereby confirming the partial mediating roles of HI and TT in the relationship between CNH and YD.

The structural model results further show that the independent variables explain 44.9% of the variance in YD with statistical significance ($P < 0.05$). According to Hair et al. [79], the adjusted R^2 value of 0.449 indicates acceptable predictive capability and practical value in explaining users' behavioral intention.

4.4. Asymmetric analysis (fsQCA)

4.4.1. Necessary condition analysis

The coverage values in Table 5 are relatively high, confirming that the conditions are relevant and meaningful for explaining the outcome [83]. The results show that all conditions - both their presence and absence (denoted by ~) - have consistency values below the 0.90 threshold suggested by Dul [84]. Notably, the consistencies for absent conditions (e.g., ~CNH, ~HI, ~TT) remain low, ranging from 0.508 to 0.536, indicating that the lack of any single factor is not a necessary condition for the outcome. Therefore, the study concludes that no single factor exists that serves as the sole mandatory factor leading to YD, supporting the view that YD results from complex interactions among multiple configurations of conditions.

Table 5. *Necessity analysis of prerequisite conditions*

	Consistency	Coverage
CNH	0.779	0.767
~CNH	0.519	0.575
HI	0.778	0.802
~HI	0.508	0.537
TT	0.736	0.742
~TT	0.536	0.579

Source: Compiled by the authors

4.4.2. Sufficient condition analysis

Table 6. *Results of sufficiency analysis of conditions leading to Continuance Intention*

	Consistency	Unique coverage	Raw coverage
CNH*HI	0,8770	0,1195	0,6673
TT*CNH	0,8484	0,0731	0,6209
TT*HI	0,8828	0,0609	0,6087
Solution coverage: 0,8013			
Solution consistency: 0,8009			
Notice: The symbol (*) denotes the logical AND operation (simultaneous combination of conditions).			

Source: Compiled by the authors

Table 6 identifies three configurations leading to YD. These configurations are evaluated using consistency to assess the reliability of the causal relationship and raw coverage to capture how empirically prevalent each configuration is [83]. Among them, CNH*HI is the dominant configuration with the highest raw coverage (0.6673), indicating that it is the most common explanatory pathway for most respondents in the sample. In contrast, TT*HI has lower raw coverage but the highest consistency, suggesting that it is the most reliable configuration for promoting YD with the highest likelihood of success. The presence of unique coverage across all three configurations - particularly TT*CNH (0.0731) - demonstrates that each pathway provides a distinct explanatory contribution rather than being entirely overlapping.

5. Recommendations and conclusion

5.1. Discussion of findings

The results of the structural model analysis confirm that HI is the factor with the most positive impact on YD, consistent with the findings of Al-Qaysi et al. [85] when affirming that functional value is the prerequisite for user retention. In addition, the mediating role test results show that the indirect effect of CNH on YD through HI is stronger than the direct effect, whereas the indirect pathway via TT is the weakest. This suggests that personalization creates meaningful value only when it enhances users' practical benefits, reinforcing Gao et al. [86] that the CNH → HI mechanism is dominant and outweighs purely affective drivers.

To further unpack causal complexity, the fsQCA results indicate that no single factor is decisive for YD. This supports Pappas and Woodside [77] regarding the complex nature of consumer behavior. The implication is that retention strategies should adopt a coordinated, multi-factor approach rather than optimizing a single component in isolation. This helps explain why high CNH alone - without sufficient usefulness or enjoyment - may still fail to sustain YD consistently.

The findings also show that the CNH*HI combination provides the most distinctive explanatory value, evidenced by the highest unique coverage (0.1195). This extends Aw et al. [87] by demonstrating that HI performs most effectively when paired with personalization. Moreover, although TT exhibits a relatively modest direct effect in the SEM results, fsQCA identifies TT as a core component in two other important configurations (TTCNH and TT*HI). This discrepancy suggests that the role of TT may not be fully captured by SEM's average net-effect estimates; in practice, TT can be decisive for certain user segments, and it may compensate for other limitations when functional value is not yet optimal.

5.2. Theoretical contributions

This study offers three key theoretical contributions.

First, it clarifies the mechanism through which CNH influences YD on e-commerce platforms by separating the cognitive and affective mediation channels. Specifically, CNH affects both HI and TT, which in turn lead to YD. This approach provides quantitative evidence supporting the argument that CNH generates not only functional value but also emotional value, both of which are important antecedents of YD [17], [88], [89].

Second, the study integrates the SOR and TAM frameworks in the context of personalized recommender systems. This integration leverages TAM's explanatory power for technology acceptance while utilizing SOR's strength in modeling internal psychological states as mediators, thereby extending the application of both frameworks to explain how CNH shapes YD on e-commerce platforms [90], [89].

Third, the study contributes contextually by providing empirical evidence from users of major e-commerce platforms in Vietnam (Shopee, Lazada, Tiki, TikTokShop) - a fast-growing emerging market with distinctive characteristics in behavior, perceived risk, trust, and platform dependence. While much existing SOR-based personalization research focuses on developed markets [38], [48], [91], [92], this study adds insights from a developing economy and helps assess the generalizability of the relationships among CNH, HI, TT, and YD under different digital infrastructures, trust levels, and shopping habits.

5.3. Managerial implications

The results indicate that HI has a stronger effect on YD than TT at the full-sample level, implying that e-commerce firms should prioritize improving the platform's functional value to increase users' HI. Several specific actions can support this objective. First, e-commerce platforms should improve recommender-system accuracy by incorporating multi-layer data into recommendation algorithms - not only at the individual level but also extending to users' social interactions and usage contexts. This can help generate recommendations that better match customers' needs [4]. Second, firms can enhance platform transparency to increase perceived usefulness and strengthen user trust [97].

In addition, fsQCA results show that TT still appears in two configurations leading to YD. This implies that, beyond functional factors, e-commerce firms should not overlook users' affective experiences. Managers should therefore design shopping journeys that are entertaining and engaging to maintain users' interest. Specifically, firms may apply gamification and promote users' social interaction on the platforms [94]. Introducing serendipitous recommendations into the system may also create novelty during shopping [93]. These approaches have been shown to be effective in enhancing TT in e-commerce settings.

5.4. Study limitations

This study has several limitations that should be addressed in future research. First, it examines personalization features across all product categories on ecommerce platforms, whereas the need for personalization may vary by product type [95]. Future studies should segment product categories to better reflect customer behavior. Second, behavior in digital environments may be influenced by user personality traits [96]. Therefore, future research should investigate users' characteristics more deeply and examine their roles in shaping YD.

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