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## **Enhancing Customer Experience and Co-creating Social Value Through Hyper-personalisation in the Fashion Industry**

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**Abstract:** Rationale behind this study was to investigate value of co-creation and customer engagement's impact on customer experience within the hyper-personalised digital setting of fashion brands. Increasing essence of conscious apparel production in response to fashion waste led us to explore AI-driven marketing strategies to provide individualised experiences to customers. Research was conducted using five independent latent variables, namely hyper-personalisation, co-creation, customer engagement, customer experience and innovative behaviour. Questionnaire was composed as a research instrument, and 414 valid responses through convenience sampling technique were collected. Analysis was run using Smartpls version 4 and SPSS version 27. Research findings illustrated significant impact of hyper-personalisation on all variables, confirming that customised interactions are essential for upgrading customer satisfaction and stimulating innovative actions. However, connection between innovative behaviour and customer engagement was insignificant, indicating that active interaction cannot be direct factor leading to inventive actions. Businesses can benefit from this study by revealing sufficient personalisation techniques. Significant impact of hyper-personalisation on digital shopping aspects highlights the need for tailored interactions to achieve better outcomes. This was the first study to examine causal link between hyper-personalisation and various aspects of shopping using Social Cognitive Theory Model, which concentrates on behavioural changes rather than periodical ones.

**Keywords:** *customer experience, hyper-personalisation, customer engagement, value co-creation, fashion brands.*

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## Introduction

As advanced technologies are modifying the functioning of organisations currently, customer-brand bonds are being changed, levelling up to a new stage of interaction. Customers are now gaining more opportunities to impact brands with their expectations and needs. Therefore, they are becoming active creators and changers of fashion trends (Rathore, 2017). This is because a product-oriented approach of value creation shifted to a customer-focused one (Tynan et al., 2010). Value creation is essential to foster an exceptional customer experience while shopping, and therefore, retailers need to engage with their clientele via all channels possible (Jain et al., 2018; Narula et al., 2022). By filling gaps in the communication, an individualised approach towards the customer can be shaped, leading to the match between the customer's product expectation and the delivered product (Jain et al., 2018; Kalia et al., 2020).

Co-creation is a novel phenomenon assisting brands in offering personalised (Lazarus et al., 2014) and innovative products (Shukla & Nigam, 2018). By providing tailored solutions, hyper-personalisation offers a unified shopping experience (Jain et al., 2021), catering to specific customer nuances. However, customer information is the main hindrance to implementing hyper-individualised practices and generating insights from this data (Kumar et al., 2019). To overcome these obstacles, artificial intelligence (AI) needs to be further introduced in the fashion industry (Rathore, 2017).

The relevance between customisation, customer experience and co-creation has been introduced previously. However, this is still a relatively unexplored field, requiring further targeted research. The research gaps that were untapped in previous studies are the paucity of exploring the overall relationship mentioned, and they are as follows (Cao et al., 2022):

### Research Gaps

- Limited research understands value and product creation procedures (Tynan et al., 2010).
- Little research was undertaken to examine multiple perspectives which create value for the customer (Tynan et al., 2010).
- AI involvement in innovating, co-creating products and boosting user engagement is not well discovered (Jain et al., 2021).
- How social and personal orientation influences brand purchase value should be further developed (Fernandes et al., 2015; Narula et al., 2022).

These gaps establish the framework for the actual study's questions and objectives, which seek to gain a deeper understanding of how fashion brands may employ hyper-personalisation via AI to leverage the social value co-creation process and to improve overall customer experience (Rathore, 2017).

### Research Questions

The current research will examine the following research questions based on the abovementioned statements:

- How can fashion brands co-create value for customers through hyper-personalised practices using artificial intelligence?
- What is the customer's perception of product innovation to obtain tailored solutions?
- What aspects of customer experience need closer attention to foster value?
- How can consumers be engaged in co-creation?

### Research Objectives

Aiming at the analysis of different factors' effects on the customer experience within hyper-personalised conditions, this research specifically reveals how innovative behaviour and engagement of customers influence novel product co-creation utilising artificial intelligence. The following are the study's objectives:

1. To examine customer innovativeness to co-create social value
2. To analyse customer experience enhancement in the context to hyper-personalisation
3. To determine customer engagement towards co-creatively developed new products through AI
4. To define the impact of hyper-personalisation on customer motives to co-create.

## **Literature Review**

### **Hyper-personalisation**

The literature review discovered numerous definitions explaining personalisation. In the fashion industry, hyper-personalisation, which is the utmost degree of personalisation, refers to the use of AI in offering individualised products to the target audience (Bagla et al., 2016). Since the introduction of technology, users are constantly seeking to customise their environments according to their views and lifestyle. Businesses, especially in the fashion sector, can employ this concept to deliver information that complies with customers' specific wants, creating an exceptional digital customer experience (Mohanna et al., 2025). Enterprises can monitor and analyse several aspects of customers' shopping behaviour, including purchase history, subscriptions, and ad engagement with the aid of data compiled online, and utilise it to upgrade performance.

### **Customer Experience**

Customer experience refers to both the objective and subjective responses individuals have during their interactions with a brand, encompassing emotional, sensory, and cognitive reactions (Atulkar et al., 2016). These experiences are shaped throughout the customer journey - from the initial search to the final purchase of products or services (Agarwal & Singh, 2018). In hyper-personalised digital environments, active customer engagement is essential, as it allows users to interact meaningfully with brand content, which in turn enhances the overall quality and memorability of the experience.

### **Co-creation**

Co-creation is widely recognised as a mutually beneficial relationship between firms and customers, where both parties actively collaborate to develop personalised products that cater to individual preferences. In this collaborative process, customers take on the role of co-creators, contributing ideas and insights that enhance product innovation. These co-creators often display a creative and participatory mindset, particularly when designing or influencing novel product offerings (Lazarus et al., 2014). Within the fashion industry, numerous scholarly investigations have highlighted the significance of customer involvement in co-creation, especially through experiential dimensions. Tynan et al. (2010), for instance, emphasise that luxury fashion consumption is not merely about product ownership but about the holistic and emotional experiences that brands create (Tynan et al., 2010). They argue that these experiential aspects form the basis of value co-creation, as customers seek meaning, identity, and personal expression through their engagement with fashion brands. Panigrahi et al. (2021) build on this by exploring how digital platforms can amplify such experiences, making it easier for customers to engage creatively with brands (Panigrahi et al., 2021). Furthermore, previous research has asserted that co-creation thrives particularly in hyper-personalised environments-contexts in which products and services are tailored to an individual's unique tastes and needs (Lee et al., 2012; Kim et al., 2010). These studies underscore that hyper-personalisation is not just a facilitator but a prerequisite for effective co-creation, as it enhances customer satisfaction and fosters deeper brand loyalty by making the co-creation experience more relevant and engaging (Uzo et al., 2026).

### **Value Co-creation**

The core concept of marketing and an essential part of co-creation is value, which is a fundamental element of co-creation, as it reflects the mutual benefits derived from brand-

consumer interactions (Lazarus et al., 2014). Brand consumption can be motivated by both personal and social value types; however, literature suggests that brands often emphasise social motivations more heavily (Fernandes et al., 2015). Fernandes et al. (2015) found that socially conscious consumers are driven by the desire to signal social status, achievement, and shared values through their brand choices, highlighting the role of social value in shaping consumer behaviour (Fernandes et al., 2015).

### **Customer Engagement**

Customer engagement refers to digital users actively interacting with businesses and other individuals to facilitate purchases, share experiences, and communicate within a virtual environment (Srivastava, 2019). It goes beyond transactional interactions to include emotional and cognitive involvement in brand-related activities. Research has also established a strong theoretical correlation between brand-customer collaboration and the creation of customer value, highlighting engagement as a key driver in this process (Bijmolt et al., 2010). Hoyer et al. (2010) emphasise that co-creation-where customers participate in designing and personalizing products or services-cannot occur without meaningful customer engagement, as it is the foundation for collaborative innovation and value development. (Hoyer et al., 2010). Similarly, Van Doorn et al. (2010) conceptualize customer engagement as a multidimensional construct that includes behavioural manifestations such as word-of-mouth, customer referrals, and participation in brand communities, all of which significantly enhance the brand's value and customer retention (Van Doorn et al., 2010). These insights underline the importance of fostering engagement as a strategic tool in digital marketing and value co-creation efforts.

### **Conceptual Framework: Social Cognitive Theory Model**

To explore the relationship between variables of customer-brand processes in highly personalised shopping conditions, a model derived from Social Cognitive Theory (SCT) of Bandura was developed (Bandura, 1986). Being a widely recognised framework used in assessing behaviour change interventions (Young et al., 2016), the SCT model clearly illustrates how the five perceptions are interlinked with each other and their position in the overall customer journey, where a brand-new innovative product with value is co-created.

SCT (Bandura, 2004) determines that hyper-personalisation, co-creation, customer experience, customer engagement, and innovative behaviour of the consumers are dependent on each other and provides a theoretical framework for a deeper comprehension of how changes in factors can remake end-users' behaviour. Moreover, hyper-personalised digital shopping settings, level of customer engagement, customer experience and the process of co-creation can alter how innovatively the consumer behaves (Bandura, 1986), with more developed hyper-personalisation leading to delivering a better customer experience.

### **Hypotheses Development**

As consumers engage with the fashion company virtually, they reveal their preferences to find more appropriate products and simplify the buying process (Bagla et al., 2016). While partnering in this process, tailoring new products to customer profiles, brands can foster benefits for the consumer, including superior compatibility, higher quality, improved customer service, experience, and enhanced communication (Bagla et al., 2016). As per the above discussion, hypothesis 1 (H1) is posited:

**H1.** Hyper-personalisation would display a direct impact on customer co-creation.

Companies track customers' information to individualise their feed, creating chances to make purchases within a shorter timeline. Customers enjoy these improvements – enhanced product suggestions, better-matching preferences (Bagla et al., 2016), and the alleviation of the mismatch diminishes cognitive tension for the customer while searching for the product (Aguirre et al., 2016). All these positive changes caused by hyper-personalisation led to a boost

in customer engagement in general (Schreiner et al., 2019). Hypothesis 2 (H2) is posited according to perceptions above:

**H2.** Hyper-personalisation would display a direct impact on customer engagement.

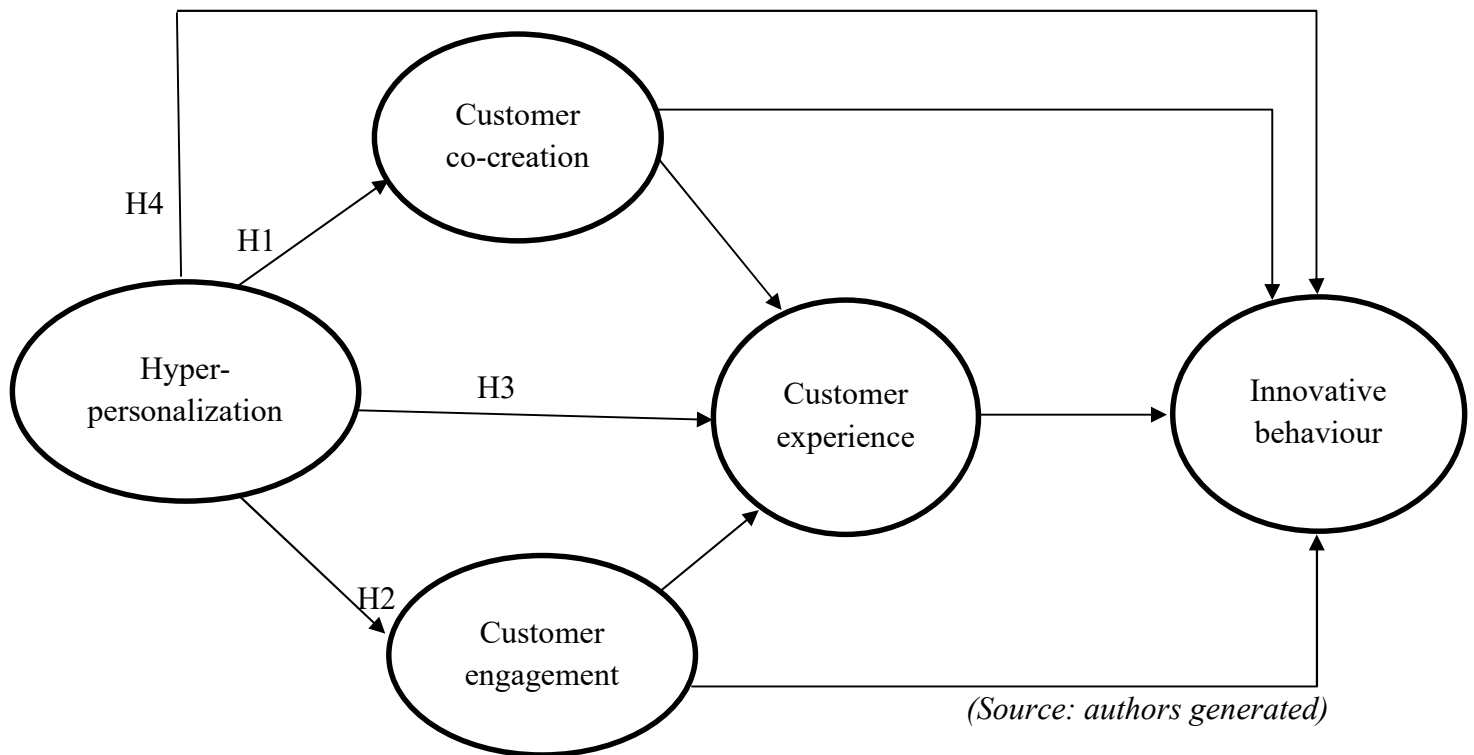
As customer expectations continue to increase, improving customer experience has turned into a difficult task for businesses. Companies should explore innovative techniques to address clients' pain points and provide a personalised customer approach, which improves their overall experience (Daqar et al., 2019). Accordingly, Hypothesis 3 (H3) is developed as follows:

**H3.** Customer experience would display a direct impact by hyper-personalisation in addition to indirect impact by customer co-creation and customer engagement.

Participating to generate value requires collaboration for product development (Lee et al., 2012), implementing fresh concepts from multiple perspectives to foster two-sided novel value (Bashir & Verma, 2017). By engaging customers in a greater manner in the co-creation, innovative concepts are expected to be recognised more by users, therefore enhancing the likelihood of success (Lazarus et al., 2014). The fourth hypothesis (H4) of the model comes from these conclusions, asserting that:

**H4.** Innovative behaviour would display a direct impact by hyper-personalisation in addition to an indirect impact by customer co-creation, customer experience and customer engagement.

*Figure 1. Research Model*



## Methodology

### Pilot Study and Measurement

Measurement metrics were primarily derived from previous academics' well-established scales to ensure the accuracy and reliability of the scale. Assessment metrics of the variables were derived from the following literature: hyper-personalisation's four items from Rahman et al. (2014), Tyrväinen et al. (2020), and Jain et al. (2018)'s studies; co-creation and engagement of

customers from Fernandes et al. (2015); customer experience's 3-item measure from Daqar et al. (2019); innovative behaviour's four-item scales by Rahman et al. (2014), Jain et al. (2021). Five-point Likert scale was employed to measure scale items.

As the research was carried out in Uzbekistan, assessment metrics were converted into Uzbek and Russian by employing the back translation method, adhering to Lin et al.'s (2019) instructions, to ensure translation accuracy. Subsequently, thorough validation of measurement items was conducted in three distinct phases. During the initial stage, a group of seven individuals was selected to review the questionnaire's clarity. Reviewers were two information technology department and two marketing department professors, as well as three PhD students with expertise in social media and fashion. After making changes to certain ambiguous questionnaire items, we conducted a preliminary test with a limited sample of 20 individuals. Consequently, we modified the wording of the questions in response to the input provided by the participants. To enhance the questionnaire, a pilot study with a large sample size of 80 individuals was held. We performed initial assessments to evaluate the dependability and accuracy of the scales and the connections between hypotheses. As a result of the positive outcomes, the questionnaire was then disseminated to a wider demographic.

### **Sample and Data Collection**

To assess the study framework, an online survey was conducted. We implemented a research instrument using Google Forms and disseminated the survey link to prospective respondents via diverse social media sites and email contacts. Due to its user-friendly interface and convenience, Google Forms facilitated the efficient collection of a substantial volume of data from a wide array of participants.

A total of 480 replies were collected during two months, spanning from February to April 2024, using a convenience sampling method. This approach was selected due to its practicality and efficiency in accessing a broad base of respondents within a limited timeframe, particularly given resource constraints and the exploratory nature of the study. After eliminating responses with consistent responses across all items or missing ones, neglected questions, and excessively quick completion times, a total of 414 valid samples were obtained. All participants were based in Uzbekistan, as the study aimed to explore consumer behaviour within a specific emerging market context where digital engagement and hyper-personalisation trends are rapidly evolving. Focusing on a single-country sample provides cultural and contextual consistency; however, it also limits the generalizability of the findings to other regions. Future research could benefit from cross-cultural comparisons to examine whether the identified patterns hold across different national or cultural settings. While convenience sampling can introduce selection bias and limit the generalizability of results, efforts were made to assess potential non-response bias. Specifically, mean values of key variables were compared between early and late respondents (Armstrong and Overton, 1977). The absence of significant differences suggests that non-response bias was minimal in this dataset. Table 1 illustrates the demographics of these respondents.

### **Results and Discussion**

The survey data was evaluated using Smartpls version 4 and SPSS version 27. Initially, the primary purpose of utilising percentile metrics and frequency distribution was to get insight into sample distribution. For the assessment of multicollinearity presence within independent variables, collinearity statistics were employed. Furthermore, scale items' dependability was evaluated by computing Cronbach's alpha coefficient values. By applying appropriate statistical techniques, the latent variables' convergent and discriminant validity were confirmed. Later, for assumptions evaluation using structural equation modelling, partial least squares methodology was utilised.

## Preliminary Univariate Analysis

### *Demographic Analysis*

Demographics consisting of age, marital status, gender, household size, education, employment and family income are depicted in Table 1. Respondents were primarily female, about 72.2% (n = 299) of the sample, while males made up the remaining 115 (27.8%). The age distribution showed that participants were mainly aged 18-24, making up 294 (71.0%) of the total. The rest of the participants were spread across the 25-34 (18.1%), 35-44 (5.3%), and 45 and above (5.6%) age groups. Regarding education, most of the respondents were bachelor's degree holders, 301 (72.7%). This was followed by those with secondary education, 64 (15.5%) and master's degree holders or higher, 49 (11.8%). The marital status of the respondents varied, with 167 (40.3%) being married, 239 (57.7%) singles, and a small percentage of 8 (1.9%) divorced.

The participants' household size was distributed as follows: a total of 56 participants, accounting for 13.5%, recorded living in a household of up to 3 people. Additionally, 227 participants, 54.8%, had 4-5 family members, while 131 participants, making up 31.6%, had 6 or more members. The participants' employment status exhibited a range of variations. Specifically, 89 participants (21.5%) identified themselves as unemployed students, 112 participants (27.1%) as employed students, 105 participants (25.4%) as employed individuals, and 53 participants (12.8%) as self-employed individuals.

The participants' family income levels were classified into four distinct groups. Out of the total number of participants, 64 individuals (15.5%) belonged to the group with an income of less than 5 million. A total of 79 players, accounting for 19.1% of the total, had earnings ranging from 5.1 million to 10 million. There were 127 participants (30.7%) in the group with a family income between 10.1 million and 20 million, and 144 participants (34.8%) in the group earning 20.1 million or more.

*Table 1. Respondents' Demographic Analysis*

| Categories     | Subcategories             | Frequency(N) | Per cent (%) |
|----------------|---------------------------|--------------|--------------|
| Gender         | Male                      | 115          | 27.8%        |
|                | Female                    | 299          | 72.2%        |
| Age            | 18-24                     | 294          | 71.0%        |
|                | 25-34                     | 75           | 18.1%        |
|                | 35-44                     | 22           | 5.3%         |
|                | 45 and above              | 23           | 5.6%         |
| Education      | Secondary                 | 64           | 15.5%        |
|                | Bachelor's degree         | 301          | 72.7%        |
|                | Master's degree and above | 49           | 11.8%        |
| Marital Status | Married                   | 167          | 40.3%        |
|                | Single                    | 239          | 57.7%        |
|                | Divorced                  | 8            | 1.9%         |
| Household size | Up to 3                   | 56           | 13.5%        |
|                | 4-5                       | 227          | 54.8%        |
|                | 6 and more                | 131          | 31.6%        |
| Employment     | Student, unemployed       | 89           | 21.5%        |
|                | Student, employed         | 112          | 27.1%        |
|                | Employed                  | 105          | 25.4%        |
|                | Self-employed             | 53           | 12.8%        |
| Family income  | Less than 5 mln           | 64           | 15.5%        |

|                   |     |       |
|-------------------|-----|-------|
| 5.1 mln - 10 mln  | 79  | 19.1% |
| 10.1 mln - 20 mln | 127 | 30.7% |
| 20.1 mln and more | 144 | 34.8% |

### *Descriptive Statistics*

The variables were generally evaluated using measures such as means, skewness, standard deviation, kurtosis, and standard errors. By taking the average of the values of the corresponding scale items, for every latent construct, the composite score was computed before analysis. Customer experience had the highest average score of 4.2601 among all the characteristics studied, standard deviation being at 0.68281. It clearly shows that participants gave a highly favourable rating to their customer experience. The data exhibits a skewness of -1.267 (standard error = .120), indicating a leftward skew, and a kurtosis of 2.464 (standard error = .239), indicating a leptokurtic distribution.

On the other hand, customer co-creation received the lowest average score of 3.8631 (SD = .97178). Although it is the lowest among the criteria, this score nonetheless indicates consumer co-creation's extremely high level. The data exhibited skewness of -.732 (standard error = .120), showing a small leftward skew. The kurtosis was .113 (standard error = .239), suggesting a distribution that is close to normal. The results indicate that participants generally gave high scores to all hidden variables. However, customer experience earned the most favourable evaluations, while customer co-creation received somewhat lower, but still positive, ratings.

*Table 2. Descriptive Statistics (n= 414)*

| Latent variables      | Mean   | Std.<br>Deviation | Skewness | Std.<br>Error | Kurtosis | Std.<br>Error |
|-----------------------|--------|-------------------|----------|---------------|----------|---------------|
| Hyper-personalization | 4.0405 | .70498            | -.845    | .120          | .386     | .239          |
| Customer Co-creation  | 3.8631 | .97178            | -.732    | .120          | .113     | .239          |
| Customer Engagement   | 4.1787 | .74264            | -1.035   | .120          | 1.489    | .239          |
| Customer Experience   | 4.2601 | .68281            | -1.267   | .120          | 2.464    | .239          |
| Innovative Behaviour  | 3.9885 | .82578            | -.669    | .120          | .262     | .239          |

### *Multicollinearity Test*

A multicollinearity test was conducted for independent variables significant correlations assessment, as these correlations could potentially affect the outcomes of the model estimate. Multicollinearity can be identified when the VIF (Variance Inflation Factor) value exceeds 5, tolerance values being below 0.1 (Hair et al., 2019). The highest VIF observed in this investigation was within the permitted values range, at 2.721. Furthermore, the tolerance values fell within the acceptable range of 0.1 and 1. Therefore, it may be concluded that the dataset did not exhibit significant multicollinearity. All four dimensions had variance inflation factor (VIF) values below 10 (hyper-personalisation = 2.71, customer co-creation = 2.499, customer engagement = 2.694, customer experience = 2.411). These findings suggest that there is no issue of multicollinearity among the formative aspects, as demonstrated by Christophersen and Konradt (2012).

*Table 3. Results of the Multicollinearity*

| Independent variable  | Tolerance | VIF   |
|-----------------------|-----------|-------|
| Hyper-personalization | .368      | 2.721 |
| Customer co-creation  | .400      | 2.499 |
| Customer engagement   | .371      | 2.694 |
| Customer experience   | .415      | 2.411 |

## **Multivariate Analysis**

### *Measurement Model Analysis*

Measurement model's study elucidates the connection between latent variables and observed or measured variables (Hair et al., 2019). For the underlying factors, numerical measurement metrics were collected from respondents. Consequently, it is necessary to assess the dependability and accuracy of the items. The suggested model was tested using the Partial Least Squares Structural Equation Modelling (PLS-SEM) technique as described by Ringle et al. (2022), utilising SmartPLS software version 4.1.0.2.

### *Convergent Reliability and Validity*

In Table 4, findings derived from the examination of the measurement model are presented, with a focus on the reliability and validity of the constructs. To assess internal consistency reliability, Cronbach's alpha (CA) and composite reliability (CR) were used. All constructs demonstrated acceptable reliability, with CA values exceeding the recommended threshold of 0.70 (Hair et al., 2019). Although the Cronbach's alpha for the customer engagement construct was slightly lower, it remained close to the acceptable level, and its CR value was above 0.70, supporting adequate reliability. Composite reliability was emphasised as it provides a more accurate estimation of internal consistency than Cronbach's alpha, particularly in structural equation modelling.

To evaluate convergent validity, factor loadings (FL) and Average Variance Extracted (AVE) values were examined. All items demonstrated factor loadings above 0.708, indicating strong individual item reliability (Hair et al., 2019). In addition, AVE values for all constructs exceeded the 0.50 threshold, confirming that each construct captured at least 50% of the variance in its respective indicators. These findings collectively support the reliability and convergent validity of the measurement model, strengthening the robustness of the study's results.

*Table 4. Results of Measurement Model Analysis*

| Latent variables      | Items | Factor loading | Cronbach alpha | Composite reliability | AVE   |
|-----------------------|-------|----------------|----------------|-----------------------|-------|
| Customer co-creation  | CC1   | 0.916          | 0.913          | 0.945                 | 0.852 |
|                       | CC2   | 0.947          |                |                       |       |
|                       | CC3   | 0.906          |                |                       |       |
| Customer engagement   | CE1   | 0.873          | 0.656          | 0.853                 | 0.744 |
|                       | CE2   | 0.852          |                |                       |       |
| Customer experience   | CX1   | 0.817          | 0.774          | 0.869                 | 0.689 |
|                       | CX2   | 0.883          |                |                       |       |
|                       | CX3   | 0.787          |                |                       |       |
| Hyper-personalization | HP1   | 0.835          | 0.809          | 0.874                 | 0.635 |
|                       | HP2   | 0.707          |                |                       |       |
|                       | HP3   | 0.801          |                |                       |       |
|                       | HP4   | 0.838          |                |                       |       |
| Innovative Behaviour  | INV1  | 0.879          | 0.888          | 0.922                 | 0.748 |
|                       | INV2  | 0.867          |                |                       |       |

|      |       |
|------|-------|
| INV3 | 0.840 |
| INV4 | 0.873 |

Given that the p-value of Bartlett's Test of Sphericity is 0.001 (Table 5), below the 5% significance level, the null hypothesis is rejected, meaning that the correlation matrix is not an identity one. The KMO Measure of Sampling Adequacy should exceed 0.70, suggesting an ample number of items for each category. Here, the KMO results are 0.936, which is acceptable.

*Table 5. KMO and Bartlett's Test*

|                                                  |         |
|--------------------------------------------------|---------|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | .936    |
| Bartlett's Test of Approx. Chi-Square            | 4560.92 |
| Sphericity                                       | 5       |
| df                                               | 120     |
| Sig.                                             | <.001   |

#### *Discriminant Validity*

According to discriminant validity, every latent variable is distinct. By comparing correlation coefficients of constructs with the corresponding square root of AVE values, the study assesses discriminant validity. Fornell and Lacker (1981) assert that AVE's square root must be over correlation values to obtain sufficient discriminant validity. AVE square root values, indicated by bolded diagonal components in Table 6, exceeded the inter-construct correlation coefficients, which are the off-diagonal elements.

The Heterotrait-Monotrait Ratio (HTMT) is a quantitative measure employed in the PLS-SEM technique to assess discriminant validity, which is confirmed when HTMT is below 0.90. It quantifies the real correlation between distinct components (Hair et al., 2019). All HTMT values, except for hyper-personalisation and customer participation, were below 0.90 in this study, as shown in Table 6. The findings demonstrated that each of the underlying factors was separate, therefore confirming their ability to differentiate from one another.

*Table 6. Results of Discriminant Validity - Fornell-Larcker Criterion*

| Latent variables      | Customer Co-creation | Customer Engagement | Customer Experience | Hyper-personalization | Innovative Behaviour |
|-----------------------|----------------------|---------------------|---------------------|-----------------------|----------------------|
| Customer Co-creation  | <b>0.923</b>         |                     |                     |                       |                      |
| Customer Engagement   | 0.686                | <b>0.862</b>        |                     |                       |                      |
| Customer Experience   | 0.597                | 0.715               | <b>0.830</b>        |                       |                      |
| Hyper-personalization | 0.732                | 0.676               | 0.692               | <b>0.797</b>          |                      |
| Innovative Behaviour  | 0.750                | 0.633               | 0.648               | 0.688                 | <b>0.865</b>         |

*Table 7. Results of Discriminant Validity – Heterotrait-Monotrait Ratio (HTMT)*

|                      | Customer Co-creation | Customer Engagement | Customer Experience | Hyper-personalization | Innovative Behaviour |
|----------------------|----------------------|---------------------|---------------------|-----------------------|----------------------|
| Customer Co-creation |                      |                     |                     |                       |                      |
| Customer Engagement  | 0.884                |                     |                     |                       |                      |

|                       |       |       |       |       |
|-----------------------|-------|-------|-------|-------|
| Customer Experience   | 0.703 | 1.001 |       |       |
| Hyper-personalization | 0.838 | 0.924 | 0.860 |       |
| Innovative Behaviour  | 0.833 | 0.827 | 0.769 | 0.798 |

### *Structural Model Analysis and Hypothesis Testing*

After the creation of the entire measurement model validation, structural model assessment occurs to validate the hypothesis (Hair et al., 2019). Stated assumptions regarding the significance of associations are evaluated and either accepted or denied through the study of a structural model (Byrne, 2013; Schumaker et al., 2004). The researchers utilised a bootstrapping technique with a subset of 5000 observations for structural model estimation (Ringle et al., 2022). Beta, t-statistics, and related p-values were presented below. T-value is significant only when it falls in the -1.96 and +1.96 values range and p-value below 0.05 in two-tailed testing (Byrne, 2013). Table 8 displays structural model study findings.

Adequacy of the model's fit was evaluated via several indices, and analysis was performed using Stata 18. Model comparison to the saturated one by chi-square test produced a statistically significant result,  $\chi^2(97) = 442.142$ ,  $p < .001$ , indicating a mismatch between data and model. However, the chi-square test for baseline and saturated models' comparison yielded a statistically significant result, with  $\chi^2(120) = 4641.269$ ,  $p < .001$ . This result aligns with the anticipated outcomes for intricate models, as stated by Kline (2016).

Root Mean Square Error of Approximation (RMSEA) was 0.093, with a 90% confidence interval ranging from 0.084 to 0.102. While this exceeds the commonly accepted cutoff of 0.08, the p-close value was significant ( $p < .001$ ), indicating that the model may still be acceptable, particularly given the large sample size and the complex nature of the model (Browne et al., 1993). This suggests that, although the fit is not perfect, it is within a tolerable range for exploratory research. The Akaike Information Criterion (AIC) had a value of 13486.547, while the Bayesian Information Criterion (BIC) had a value of 13707.969. These values serve as a foundation for comparing models. While these absolute values do not indicate fit quality on their own, they become meaningful when comparing alternative or nested models-lower values suggesting better relative model fit (Burnham et al., 2004).

Other fit indices provided stronger evidence of model adequacy. The Comparative Fit Index (CFI) was 0.924, whereas the Tucker-Lewis Index (TLI) was 0.906. Both exceeded the recommended threshold of 0.90, indicating that the model has a good level of fit and that the hypothesised relationships in the model correspond well with the observed data (Hu et al., 1999). Similarly, the Standardised Root Mean Square Residual (SRMR) was 0.042, well below the 0.08 threshold, further supporting the model's suitability (Hu et al., 1999). Furthermore, the Coefficient of Determination (CD) obtained a value of 0.941, indicating that the model accounts for a substantial proportion of variance in the endogenous constructs, demonstrating strong explanatory power.

*Table 8. Results of Structural Model Analysis*

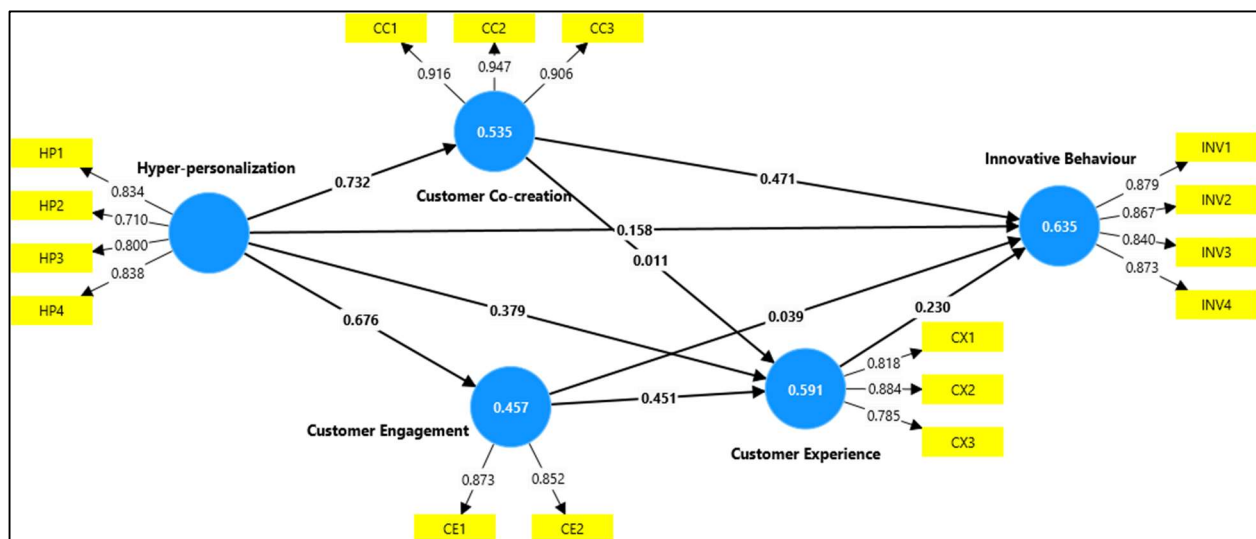
| Paths                                        | Beta  | T statistics | P values | 95%CI |       | Results         |
|----------------------------------------------|-------|--------------|----------|-------|-------|-----------------|
|                                              |       |              |          | LL    | UL    |                 |
| Customer Co-creation -> Customer Experience  | 0.011 | 0.184        | 0.854    | 0.101 | 0.125 | Not significant |
| Customer Co-creation -> Innovative Behaviour | 0.471 | 8.706        | 0.000**  | 0.364 | 0.572 | Significant     |
| Customer Engagement -> Customer Experience   | 0.451 | 6.985        | 0.000**  | 0.322 | 0.574 | Significant     |

|                          |       |        |         |       |       |             |
|--------------------------|-------|--------|---------|-------|-------|-------------|
| Customer Engagement ->   |       |        |         | -     |       | Not         |
| Innovative Behaviour     | 0.039 | 0.628  | 0.530   | 0.081 | 0.158 | significant |
| Customer Experience ->   |       |        |         |       |       | Significant |
| Innovative Behaviour     | 0.230 | 4.205  | 0.000** | 0.120 | 0.335 |             |
| Hyper-personalisation -> |       |        |         |       |       | Significant |
| Customer Co-creation     | 0.732 | 24.089 | 0.000** | 0.663 | 0.783 |             |
| Hyper-personalisation -> |       |        |         |       |       | Significant |
| Customer Engagement      | 0.676 | 19.311 | 0.000** | 0.600 | 0.739 |             |
| Hyper-personalisation -> |       |        |         |       |       | Significant |
| Customer Experience      | 0.379 | 5.221  | 0.000** | 0.233 | 0.522 |             |
| Hyper-personalisation -> |       |        |         |       |       | Significant |
| Innovative Behaviour     | 0.158 | 2.799  | 0.005   | 0.048 | 0.268 |             |

Note: \*\*p<0.01, \*p<0.05, based on a two-tailed test; t=1.96

Findings of Table 8 demonstrate that hyper-personalisation had a substantial impact on Customer Co-creation ( $\beta=0.732$ ,  $p<0.001$ ), Customer Engagement ( $\beta=0.676$ ,  $p<0.001$ ), Customer Experience ( $\beta=0.379$ ,  $p<0.001$ ), and Innovative Behaviour ( $\beta=0.158$ ,  $p<0.05$ ), hence confirming Ha1 and Ha2. The study revealed that Customer Co-creation had a substantial, favourable influence over Innovative Behaviour ( $\beta=0.471$ ,  $p<0.001$ ), thereby confirming Ha3. The study also revealed Customer Engagement's notable positive effect on Customer Experience ( $\beta=0.451$ ,  $p<0.001$ ). Nevertheless, there was no substantial impact on Innovative Behaviour ( $\beta=0.039$ ,  $p=0.530$ ), partially supporting Hypothesis 4. Furthermore, there was a significant correlation between Customer Experience and Innovative Behaviour significant link was noted ( $\beta=0.230$ ,  $p<0.001$ ), as a confirmation of Hypothesis 4.

Figure 2. Structural Model Diagram



(Source: authors generated)

### The Assessment of Prediction

The ability of the exogenous constructs to predict is determined by a variety of metrics (Hair et al., 2019), including R<sup>2</sup>, f<sup>2</sup>, Q<sup>2</sup>, as well as the magnitude and significance of path coefficients.

### Coefficient of Determination (R<sup>2</sup>)

Coefficient of determination, commonly referred to as R<sup>2</sup>, is the metric that quantifies a structural model's explanatory capability used in Partial Least Squares (PLS). The coefficient

is bounded between 0 and 1. A bigger value of R2 indicates a more accurate prediction of the endogenous constructs (Hair et al., 2019). R2 quantifies the degree to which the structural model used in PLS can explain the data, with values between 0 and 1. More R2 values suggest more predictive accuracy of endogenous constructs, with significant (0.75), moderate (0.50), and weak (0.25) explanatory ability. Table 9 illustrates endogenous latent variables' R2 values in the model: Customer Co-creation (0.535, adjusted 0.534), Customer Engagement (0.457, adjusted 0.456), Customer Experience (0.591, adjusted 0.588), and Innovative Behaviour (0.635, adjusted 0.632). Findings suggest the model's reasonable capacity to explain and predict Customer Co-creation, Customer Engagement, and Customer Experience. Specifically, it explains 53.5%, 45.7%, and 59.1% of the variations in these factors, respectively. Moreover, the model demonstrates significant explanatory capability for Innovative Behaviour, accounting for 63.5% of its variability. Therefore, the structural model exhibits robust predictive capacity, especially for Innovative Behaviour, thereby confirming its efficacy in the research environment.

*Table 9. R-Square of the Endogenous Latent Variable*

| Construct            | R Square | R-square adjusted | Comment     |
|----------------------|----------|-------------------|-------------|
| Customer Co-creation | 0.535    | 0.534             | Moderate    |
| Customer Engagement  | 0.457    | 0.456             | Moderate    |
| Customer Experience  | 0.591    | 0.588             | Moderate    |
| Innovative Behaviour | 0.635    | 0.632             | Substantial |

#### *Effect size ( $f^2$ )*

Effect size, symbolised as  $f^2$ , is that which is utilised to evaluate the impact that the removal of the predictor construct has on endogenous or outcome constructions. To put it another way, the  $f^2$  value indicates the potential fluctuations that may occur in the endogenous construct following the elimination of any of the exogenous constructs. It can be deduced that the  $f^2$  values depict medium (0.02) and high (0.15) effects, respectively (Table 10).

*Table 10. Effect Size ( $f^2$ )*

| Constructs                                    | f-square | Effects    |
|-----------------------------------------------|----------|------------|
| Customer Co-creation -> Customer Experience   | 0.000    | Very small |
| Customer Co-creation -> Innovative Behaviour  | 0.242    | Small      |
| Customer Engagement -> Customer Experience    | 0.231    | Small      |
| Customer Engagement -> Innovative Behaviour   | 0.002    | Very small |
| Customer Experience -> Innovative Behaviour   | 0.059    | Small      |
| Hyper-personalisation -> Customer Co-creation | 1.153    | Large      |
| Hyper-personalisation -> Customer Engagement  | 0.842    | Large      |
| Hyper-personalisation -> Customer Experience  | 0.143    | Small      |
| Hyper-personalisation -> Innovative Behaviour | 0.024    | Small      |

#### *Predictive Relevance ( $Q^2$ )*

When  $Q^2$  exceeds 0.00, path model predictive accuracy is acceptable (Hair et al., 2019). Table 11 displays construct cross-validated redundancy ( $Q_{\text{predict}2}$ ) values for endogenous constructs, which are all above 0.00, demonstrating the model's predictive significance.  $Q_{\text{predict}}$  values are 0.531 for Customer Co-creation, 0.452 for Customer Engagement, 0.473 for Customer Experience, and 0.469 for Innovative Behaviour. These values suggest strong predictive accuracy of the model for these constructs, particularly for Customer Co-creation, which has the highest  $Q_{\text{predict}2}$  value, indicating the model's robust ability to predict this construct. Overall, the  $Q_{\text{predict}2}$  values confirm the model's effective predictive performance across all key constructs.

According to Hair et al.'s 2019 research, the predictive accuracy of the path model is satisfactory when the  $Q^2$  value is greater than 0.00. Table 11 represents construct cross-validated redundancy ( $Q^2_{\text{predict}}$ ) values for the endogenous constructs. All of these numbers are more than 0.00, making the model predictively relevant.  $Q^2_{\text{predict}}$  is as follows: 0.531 for Customer Co-creation, 0.452 for Customer Engagement, 0.473 for Customer Experience, and 0.469 for Innovative Behaviour. Customer Co-creation, which has the highest  $Q^2_{\text{predict}}$  value, indicates that the model has a robust capacity to predict this construct. These results demonstrate the model's considerable predictive accuracy for these constructs, particularly for Customer Co-creation. The  $Q^2_{\text{predict}}$  values, taken as a whole, provide evidence that the model possesses significant predictive performance across all of the main constructs.

*Table 11. Construct Cross-Validated Redundancy ( $Q^2_{\text{predict}}$ )*

| Endogenous construct | $Q^2_{\text{predict}}$ | Comment                       |
|----------------------|------------------------|-------------------------------|
| Customer Co-creation | 0.531                  | Moderate predictive relevance |
| Customer Engagement  | 0.452                  | Moderate predictive relevance |
| Customer Experience  | 0.473                  | Moderate predictive relevance |
| Innovative Behaviour | 0.469                  | Moderate predictive relevance |

The current study's novelty was the bridging of a critical gap concerning hyper-personalisation and its impact on various facets of customer behaviour, including customer co-creation, engagement, and innovative behaviour. Although the advantages of general personalisation have been extensively explored, the indirect effects and mechanisms of hyper-personalisation have lagged far behind. The key contribution of this study is that it offers insights grounded in literature review, showing how hyper-personalisation can drive customer innovation and better engagement, and conveying actionable strategies for businesses to improve their marketing efforts. Currently, the obtained data shows that hyper-personalisation has a positive impact on factors like experience and engagement of the customer, which are vital for consumer satisfaction and perceived value.

However, the relationship between customer engagement and innovative behaviour was found to be statistically insignificant ( $\beta = 0.039$ ,  $p = 0.530$ ). This suggests that, while engagement enhances customer experience, it may not directly stimulate innovative actions. Innovative behaviour is likely influenced by additional factors such as intrinsic motivation, autonomy, or contextual conditions that support creativity and proactive participation (Hair et al., 2019; Byrne, 2013). It is also possible that the form of engagement assessed—primarily emotional or relational—does not sufficiently activate the cognitive processes required for innovation. These findings highlight the complexity of innovation and suggest the need for further research into mediating or moderating variables that may shape this relationship.

This research also enhances existing academic offerings with significant data on the advantages of hyper-personalisation in customer interactions. These findings support the notion that personalised strategies are crucial for businesses aiming to upgrade customer engagement and foster innovation. Moreover, the study's insights challenge previous assumptions about the direct link between engagement and innovation, suggesting that a more nuanced understanding of these links is needed. For example, hyper-personalisation's significant influence on co-creation ( $\beta=0.732$ ,  $p<0.001$ ) and customer engagement ( $\beta=0.676$ ,  $p<0.001$ ) highlights personalised experience's critical role in driving customer involvement and interaction (Hair et al., 2019). Furthermore, hyper-personalisation also showed a substantial influence over customer experience ( $\beta=0.379$ ,  $p<0.001$ ) and innovative behaviour ( $\beta=0.158$ ,  $p<0.05$ ),

confirming that tailored interactions are crucial for enhancing overall customer satisfaction and promoting innovative actions (Ringle et al., 2022).

SCT provides a valuable paradigm comprehending the connections among hyper-personalisation, consumer co-creation, engagement, and inventive behaviour. SCT claims human behaviour to be shaped by the interplay of personal variables, actions and environmental influences, as proposed by Bandura in 1986. Within the scope of our research, hyper-personalisation functions as an ambient stimulus that moulds client behaviour by fostering a more captivating and engaged encounter.

The beneficial effect of hyper-personalisation on customers collaborating in creating value can be understood via SCT. When customers receive experiences, it boosts their belief in their abilities and motivation, encouraging them to actively participate in co-creating value (Bandura, 1991). This mirrors SCT's focus on determinism, where tailored interactions shape customer perceptions and behaviours, ultimately strengthening engagement (Bandura, 1986). Nevertheless, the lack of a correlation between customer engagement and innovative behaviour suggests that while engagement is necessary, it may not be sufficient alone to drive innovation. According to SCT, for innovation to occur, individuals need not only to be engaged but also to have the self-confidence and creative environment required to turn engagement into innovative actions. This highlights the necessity for further investigation into the circumstances under which engagement leads to innovation.

Hyper-personalisation has an impact on customer co-creation, engagement and experience. For example, its advantageous impact on customer co-creation ( $\beta=0.732$ ,  $p<0.001$ ) as well as engagement ( $\beta=0.676$ ,  $p<0.001$ ) represents personalised approaches' effective encouragement for customer involvement and satisfaction (Hair et al., 2019).

## **Conclusion**

### **Managerial Implications**

By incorporating Social Cognitive Theory, this study serves as a foundation for comprehending the interactions between hyper-personalisation and customer behaviours. It clarifies how customised experiences contribute to increased levels of customer engagement and loyalty. The study questions established knowledge by demonstrating that mere engagement might not be enough to stimulate behaviour ( $\beta=0.039$ ,  $p=0.530$ ). This calls for a deeper exploration of the factors that enable innovation, highlighting the need for additional motivational and contextual factors. Businesses, especially in fashion-related fields, looking for sufficient personalized techniques can benefit from the findings by employing hyper-personalization concept to offer products and services tailored to specific customer needs, as substantial influence of hyper-personalization on customer experience ( $\beta=0.379$ ,  $p<0.001$ ) and innovative Behaviour ( $\beta=0.158$ ,  $p<0.05$ ) underscores value of tailored customer interactions in achieving better outcomes.

### **Practical Implications**

Current research has contributed to the literature by demonstrating its causal relationship between the variables. Jain et al. (2018) investigated hyper-personalisation by employing the Technology Acceptance Model, in comparison to the SCT model in the current study, to comprehend consumer experience for hyper-personalisation via big data and analysis. Its application could not comprehend the extent of the relation between the variables. Hence, SCT is a better fit to investigate the causal relationships rather than just the existence of the link between hyper-personalisation, customer engagement, experience, co-creation and innovative behaviour.

### **Study Limitations and Scope for Future Research**

Current research's major constraint is its cross-sectional methodology, which collects data only at a specific time. This design cannot observe and track patterns and shifts in client behaviour over time. Consequently, even though correlations between hyper-personalisation and customer behaviours might be established, prevalence is not causality. Therefore, upcoming research might need a longitudinal design to assess change in time, which might formulate a greater understanding of how hyper-personalisation impacts customer engagement and innovation over time. The study has one more limitation, which is based on the sample on which the research was conducted. These are people from one country and a specific demography, Uzbekistan, which also imposes a significant limitation to the current research. The respondents' cultural and economic background may affect their attitudes toward hyper-personalisation. For that reason, it is imperative to conduct this research in various geographical and cultural areas to confirm its results and affirm that the implications can be generalised across markets and demographics. The data for this investigation were gathered via self-reported questionnaires, which are subject to biases like social desirability and recall. The participants may, for example, overestimate their engagement or innovative behaviour for hyper-personalisation to represent themselves in a positive light. Future studies could attempt to minimise these biases and provide a more accurate assessment of the impacts of hyper-personalisation by combining self-reported data with an objective indicator, such as behavioural data from customer interactions. In conclusion, while the sample of 414 is adequate for statistical analysis, a more substantial and diverse sample would generate more robust results. Additionally, the described measurement method would increase the power of analysis and allow for more nuanced investigations with consideration of additional subpopulations. Future research needs to aim to include a broader demographic to boost the representativeness of findings.

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