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Exploring Dynamic Brand Experience through Co-Creation and E-WOM: Implications for Consumer Equity in Social Media Marketing

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ABSTRACT

Within the framework of social networks, this research investigates the function that dynamic brand experience may play as a marketing tool for companies. We want to know how co-creating value impacts the dynamic brand experience, based on the source and motive. The study also examines the link between dynamic brand experience and consumer equity, as well as the moderating impact of electronic word-of-mouth (E-WOM). A dynamic brand experience may be positively impacted by the source and motive of value co-creation. Customers' brand equity and dynamic brand experience are also positively correlated. As for the link between a dynamic brand experience and consumer equity, E-WOM serves as a moderator.

Introduction

Experiential marketing must be included in the design process for companies in today's increasingly competitive and dynamic marketplace (Batat, 2024). Companies must involve customers in their marketing initiatives if they wish to differentiate themselves and create a strong competitive position. Therefore, modern companies must use experiential marketing to design and implement marketing strategies. Social networking sites also provide a great opportunity for customers to experience the brand or services and interact with hundreds or thousands of people regarding goods, brands and corporations (Garner & Mady, 2023).

Information overload is a hallmark of the modern Internet world. Markets are information-rich, dynamic, and fast-moving (Waseel, Zhang, Zia, et al., 2024). As a result, brand experience varies in strength and duration, and brand development and consistency are qualities of experience. Manufacturers and sellers must optimize, and customers must profit at each stage of a consumer's consumption journey. When it comes to consistency, it is described as the perception of a consumer's whole brand experience (both online and offline) (Madakam & Tripathi, 2021). Consumers' real experiences, sentiments, cognitions, and behavioral responses to a brand have been the topic of previous research (Sharief & Elsharnouby, 2024). However, few studies have examined consumers' social media brand experiences from the viewpoints of phase and consistency (Garner & Kim, 2022; Tirpude, 2022). Because of that, this study conceptualizes the interactivity and real-time brand experience with rich information as a dynamic brand experience, a notion consisting of two dimensions: phase and consistency. Although a great deal is known about how brand experience influences customers, less is understood about why and how consumers make decisions about their purchases.

Customers' brand-themed interactive experience may be enhanced through value co-creation, a sort of product development conducted by both the firm and the customer jointly (Al-Adwan et al., 2025). Numerous companies (including Haier, the world's largest home appliance brand; MI, a leading technology innovator; and Tesla Motors, a pioneering electric car company) have developed innovative interactive platforms on social networks, allowing customers to experience the convenience of product information acquisition and communication through real-time interaction with business representatives (Jain et al., 2021). A firm's brand value will increase as a result of timely feedback and ideas from users (current or future consumers) (Dubbelink et al., 2021). From a value co-creation viewpoint, this study examines the impact of dynamic brand experience in influencing the success of corporate products, Value co-creation is examined in terms of its source and motive. Understanding these components of value co-creation can assist companies in developing effective experiential marketing strategies for their products and services.

This study examines elements that influence customers' dynamic interactions with brands in social networking environments, as well as their impact on customer equity. E-WOM is used as a moderator in our research, and we anticipate that the varied E-WOM on social networking forums can improve or decrease the degree to which dynamic brand experience affects consumer equity, respectively. On the theoretical side, it examines how dynamic brand experiences impact consumer equity from a value co-creation viewpoint. Therefore, this study extends prior research on the consequences of dynamic brand experience in social networking environments by developing a theoretical model of dynamic brand experience, value co-creation, and its implications. To preserve and expand their client equity, this research guides the managers on how to execute consumer-driven brand experiences through value co-creation activities. Based on the above discussion, this study suggests investigating the following research questions,

- Is there any association between brand experience and brand equity?
- Is there any association between the source of value co-creation and brand experience?
- Is there any association between the motivation of value co-creation and brand experience?
- Does word of mouth moderate the association between brand experience and brand equity?

Literature Review

Value Co-creation

An important use of web-based technology is to help develop new goods or to gather suggestions for improving existing ones (Saha et al., 2022). A group of customers, the general public, can create product ideas through interactive engagement on web-based social platforms such as Facebook, Instagram, and blogs (Carvalho & Alves, 2023). Value co-creation in social networking environments, according to (Sohaib & Han, 2023), comes from knowledge sharing, engagement, and equality. Shared information and knowledge are the basis for value co-creation, and businesses' long-term viability is dependent on their capacity to share them. Customer evaluation of the experience is based on the acquisition of relevant knowledge and information, resulting in the generation of new value needs, while companies manage and create new possibilities for value co-creation by utilising organisational learning (Sen et al., 2023). In this interactive and dynamic process of value co-creation, customers are involved in the creative process and communicate with the firm.

Value co-creation in interactions between enterprises and customers encourages communication and provides a platform for both sides to take part in value creation. In other words, great consumer contact might generate entirely new types of products or value activities (Waseel, Zhang, Shehzad, et al., 2024). As a result, engagement on the social networking platform is a location where value co-creation and co-creation experience occur, and interaction promotes information flow, knowledge transfer, and value development (Zheng et al., 2025). Consequently, equity can estimate the value of the company's consumers. Customer relationship management.

Many studies hold that a company's ability to turn a profit is a critical factor in its success. Customers are the primary determinant of a firm's identity, not its brand or goods. So that their experience or value co-creation activity is a fundamental equity component (Solakis et al., 2024). Social networking value co-creation has been a popular marketing approach due to its efficacy. Yet very few studies have explored the source of value creation in computer-mediated contexts. The purpose of this paper is to fill this research vacuum by examining three particular sources of value co-creation: knowledge sharing, interaction, and equity. Hypotheses describe the function that each of these factors plays in creating a dynamic brand experience.

Dynamic Brand Experience

When consumers are exposed to brand-related stimuli such as brand recognition and packaging, behavioural responses are created. In an accumulation process, the customer's brand experience is similar to the consumer-brand connection dynamic process (Yu et al., 2021). Non-linearity is a feature of brand experience, according to (Motta-Filho, 2021). They want consistent experiences across platforms as more customers switch to multichannel purchasing. In terms of long-term exposure, consumers' certainty of brand attitude will grow if the information they receive from multichannel brand experiences is more consistent, whereas inconsistent brand experiences would create conflicting information and reactions. Brand experience is also phased and cumulative (Siebert et al., 2020) and consumer's connection with a brand develops gradually, just like a person's relationship with another person. More brand experiences lead to more purchases or judgments made by customers based on brand knowledge acquired from various experiences. Brand experience measurement should be comprehensive and process-oriented, dynamically collecting customer decisions or comments at every point of interaction with the company. The dynamics of brand experience in the setting of social networks have received little investigation. Because of the growing relevance of experiential marketing, the customer's position shifts from passive recipient to active participant. Accordingly, this study defines the "dynamic brand experience" as the psychological and emotional state of interaction between various stakeholders at different phases of brand development and consumption, concerning the relevant product issues at each instant of contact (Motta-Filho, 2021) and (Yu et al., 2021) suggested the phase and consistency dimensions of brand experience, which are used in this study to quantify and show the dynamic character of brand experience. Customers and companies can benefit from a shared understanding of information through knowledge sharing. Firms may use technology to improve their connections and operations by sharing information gained from actual encounters (Becker & Jaakkola, 2020). This type of contact also allows customers to get brand information and expertise about a product, which may help them develop a strong and lasting relationship with the brand. Clients can be viewed as separate equity in the sense that their experiences or worth can be exploited as a source of corporate profit, constituting a key part of corporate equity. As a result, consumers' unique experiences are being enhanced through communication tools employing social networks. Customers may conduct brand-based conversations on social networking platforms, receiving necessary product information promptly and exchanging product experience, creating a unique dynamic brand experience.

H1: Source of value co-creation positively influences the dynamic brand experience

(Yu et al., 2021) has proposed that motivation explains why individuals behave in specific ways and what initiates their conduct. Understanding what motivates customers to participate in value co-creation might also help companies strategically manage their contacts with consumers in a way that produces greater value for both the consumers and the enterprises. Customers' economic interests are represented through financial benefits (e.g., cash rewards and fortune draws) in addition to price and perceived value. (Yu et al., 2021) found that financial incentives or economic advantages were key elements in enticing customers to join in value co-creation launched by the firm. This, in turn, influenced consumers' brand experience and brand value perception. The growing network of contacts and friendships is necessary for social integration, and customers are to join in value co-creation. Consumers engage in virtual interactions because they're curious about the social consequences of such activities (Cheung et al., 2021). Active engagement in value co-creation, according the (Kaur et al., 2024), may produce pleasant sentiments and joyful experiences and argues that value co-creation activities increase consumer interest by integrating their information, knowledge, skills, and abilities, as well as exercising their wisdom and potential in activities. Due to the thrill and experience of participating in this process, consumers are more likely to be curious about products and brands.

H2: Motivation of value co-creation positively influences the dynamic brand experience.

Brand Equity

As a confluence of marketing, finance and stakeholder value, brand equity has been the focus of much research. Brand equity signals are essential in decision-making under uncertainty for customers. It may also be defined by the differential reaction to marketing efforts that a product gets following brand recognition (Oliveira et al., 2023). The value of a brand varies depending on the type of goods. A greater perceived quality dimension would apply to technological goods, according to a recent study. Additionally, technological goods have a shorter life cycle, highlighting the need for brand recognition to acquire equity. Consumers' differing responses to a focused brand and an unbranded product when both have the same marketing stimuli and product features (Haudi et al., 2022). If residual problems remain, the one-dimensional metric is preferable. Researchers observed that single dimension brand equity scales outperformed multi-dimensional brand equity scales in evaluating brand equity, whereas (Oliveira et al., 2023) discovered similarities between multi and single dimension brand equity scales.

Therefore, it can be hypothesised that,

H3: Dynamic Brand Experience positively influences Brand Equity

Word of Mouth

Consumer-generated content has become a significant driving factor in online markets, along with the popularity of social networking. Word-of-mouth (WOM) is the capacity of a potential or existing customer to transmit assessment information, views, and associated knowledge about a certain product to others. Traditional word-of-mouth (WOM) is a verbal communication method that has limits (Donthu et al., 2021). Electronic word-of-mouth (EWOM) is a new verbal communication method that is created over the Internet. Persons (transmitters) influence other individuals (recipients) through conveying stimuli. (e.g., linguistic symbols). As a result, material shared on social networks is more popular and seen as more valuable, such as extending one's knowledge base and getting professional advice (Dewi et al., 2022). SRT argues that human behaviour is a learnt reaction to a stimulus. When consumers are exposed to specific stimuli (such as EWOM), they are more likely to behave rationally. In the case of E-WOM, for example, high-quality and trustworthy E-WOM can assist customers in making better informed judgements about the quality of items, which in turn influences their buying behaviour. The authors of Park and Lee (2008) stated that consumers are more likely to favour a product if there are more positive evaluations available about it. In addition, the brand's image improves as the amount of favorable E-WOM increases. Researchers have also shown that unfavorable E-WOM information increases customers' uncertainties and concerns due to their weak cognitive knowledge structure, which can negatively affect their evaluations of companies and purchase intention.

H3: Word of Mouth mediates positively between Dynamic Brand Experience and Brand Equity

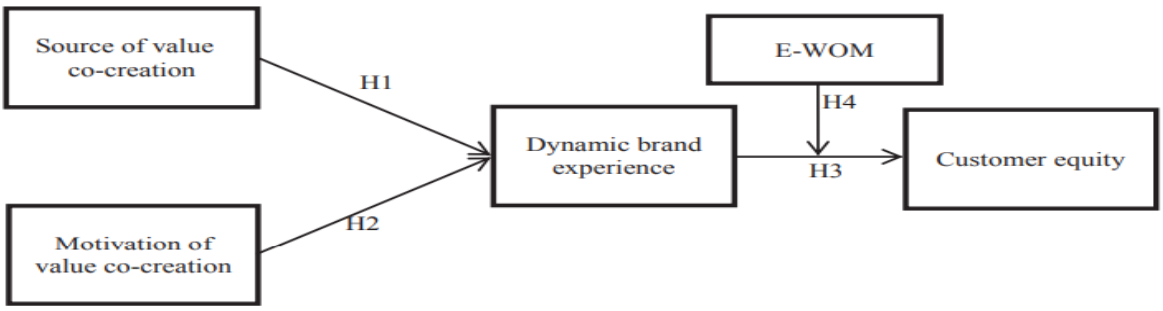

Fig. 1. Proposed model.

Methodology

The overall plan or structure which is used to conduct the entire study is included here in the research design. The current research design will focus on the individual design. We will examine the relationship between dependent and independent variables and their impact on an individual level. There are many reasons to focus on individual level instead of group and organization approach (Fox et al., 2022): (1) individual approach is less expensive, (2) because this approach allow researchers to involve more respondents to produce greater response, (3) there is no complication of data in analysis process, (4) and the last strong reason is that most of the researchers focuses on this individual approach. Survey method is a technique used to collect data from the respondent (single respondent), such as a questionnaire, it is from the field of applied statistics (Li et al., 2022). In the current paper survey method is used to collect data from single respondent. we are using the survey method because of its various advantages the 1st advantage is that it is a very cost-effective technique used to collect data. The 2nd advantage is that it allows us to collect data from large sample of population. The 3rd is it must be standardized. The 4th advantage is through survey method we can collect data easily from the respondendent.

Common method variance and Sampling frame

Common method can be defined as “Variance that is attributable to the measurement method rather than to the construct the measures are designed to represent” (Podsakoff et al., 2024). In common method variance data will also be collected from external managers or supervisors (who are not the members of the team).

Population frame refers to the list of all elements in the population through which the sample is selected. A good sampling frame encapsulates all sample units in the population, but it may not be completely available, so researchers spend time and effort collecting data from the current population. In this current research, simple random sampling is used. The basic advantages of this sampling are the availability of data. We can collect data easily from anywhere or everywhere. Moreover, it is time time-saving technique, although this method is less expensive. They have greater touch with the virtual branding community established by the businesses, and they have regular interactions with enterprises as well as rich social media experiences. The size of the sample should be appropriate so that the result can be generalized over the whole population. A number of respondents should be chosen from the method given by Sekaran table of sampling. The population of the study will be 1000 elements, then according to the Sekaran table sample should be 440, which represents a 95% confidence level with a margin of error of 3.5%.

Research instrument

The questionnaire is used as the research instrument in the current study. By reviewing different articles, scales will be used from these sources. Every variable has different scale items. To ensure the scale's reliability and validity most suitable items will be used.

Source of value co-creation	10	(Ranjan & Read, 2016)
Motivation of value of co-creation	4	(Nambisan & Baron, 2009)
Dynamic Brand Experience	18	(Jiang & Benbasat, 2004)
E- WOM	03	(Rust et al., 2004)

To ensure the instrument was reliable, the internal consistency method was employed using a reliability coefficient attained by computing Cronbach’s alpha for every factor in the study (Ahmad et al., 2019). All multi-item scales used in the study attained high internal scale reliability with Cronbach’s alpha standardized values ranging from 0.754 to 0.935. For the reliability of each factor, Cronbach’s alpha should be above 0.7; thus, the results shown in table 3.8 suggest that all these scales are reliable and can be employed in the main study.

Table Error! No text of specified style in document.**-1:** Scale Reliability

Scale	Cronbach Alpha
Source of Value Co-creation	0.859
Motivation of Value Co-creation	0.754
Dynamic Brand Experience	0.935
Customer Equity	0.845
Word of Mouth	0.770

Methods of Analysis

The analysis methods employed for addressing the research questions of the present study range from descriptive statistics, reliability test, and correlation analysis to advanced structural equation modeling (SEM). In the first phase of data analysis, Statistical Package for the Social Sciences

(SPSS) was used for preliminary univariate statistical analysis (Sürücü et al., 2023). An attempt was made to screen the data. Data screening refers to the process of assessing whether the data is free of outliers, normally distributed, and ready to be used. In the next step, SEM was employed to confirmatory factor analysis (CFA). Statistical Package for the Social Sciences has three advantages: (1) it allows users to import or export data sets that can be viewed in rows and columns; (2) the window that presents the result output has edit options; and (3) the window showing charts and graphs can be customized. On the other hand, AMOS incorporates a user-friendly graphic interface with an optimal computing engine for SEM.

Reliability Analysis

There are two methods to determine the reliability of a construct test-retest method and the internal consistency method (Bergmann et al., 2022). Test-retest method denotes the degree of consistency among individual responses at two different times. The aim of the test-retest method is aimed "to ensure that responses are not too varied across periods so that a measurement taken at any point in time is reliable (Willems et al., 2023). This method represents the degree to which the items of the scale are intercorrelated at a single point. Internal consistency "estimates reliability based on the average correlation among items within a test". The internal consistency method was deemed appropriate for evaluating the instrument's reliability because the data was collected at a single point. In the next step the coefficient alpha was examined. It signifies the internal consistency of items from the measurement scale. For the construct validation coefficient alpha is considered as one of the most important statistical analysis units. Cronbach's alpha with a cut-off value of 0.70 was used to determine the reliability of each research variable.

Validity

Once the reliability of all the scales was attained, instrument validation followed. *"Validity represents the degree to which the instrument measures the research constructs"*. Generally, validating a measurement instrument incorporates two methods: construct validity and convergent validity. To assess the instrument validity, content validity, convergent validity and discriminant validity were performed.

Content validity/ Face validity

Content validity is also known as face validity. Content validity indicates how well all the dimensions underlying a concept have been defined. Content validity can be assessed in two ways. First, it can be assessed numerically since it is a subjective measure depending on the researcher's judgment. Secondly, it can also be attained through an extensive literature review of underlying items evaluated by academics. The current study adopted the second method to attain content validity (Alamer & Alsagoafi, 2023). The instrument was developed with well-established measurement items in light of previous literature, combined with the expert opinion of academicians.

Convergent validity

Generally used in behavioral sciences, studying the parameters of convergent validity denotes the degree to which the various measures of a construct that are theoretically related are correlated (Alamer & Alsagoafi, 2023). In this study, convergent validity was assessed by examining the measurement model. In other words, it was determined if the estimated coefficient on its posited construct factor is significant or not (Anderson & Gerbing, 1982). In addition, the Bentler-Bonett coefficient was used to assess convergent validity. A threshold value of 0.90 was set as an indicator that convergent validity has been achieved.

Statistical Procedure

In the next step, factor analysis was employed to determine the relationship among the items in order to classify distinct items in terms of respective factors. The present study used the two types of factor analysis: Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA).

Exploratory Factor Analysis

In factor analysis, it is made to mix several intercorrelated variables under one or more general variables. The goal of factor analysis is to reduce "the dimensions which are supposed to underlie the old ones." From a practical viewpoint, EFA attempts to investigate collected data and extract underlying factors in order to best present the data. Thus, the model generation began with exploratory factor analysis to confirm the measurement model. Statistical Package for Social Sciences version 19.0 was used to conduct principal component factor analysis with promax rotation and maximum likelihood estimation. Subsequently, the "Bartlett test of sphericity" and "measurement of sampling adequacy" (MSA) were performed. The Bartlett test of sphericity highlights the significance of overall correlation among the constructs. Measurement of sampling adequacy, which denotes the intercorrelation among the variables, was measured by utilizing the Kaiser-Meyer-Olkin (KMO) statistics (Legate et al., 2023). The data is assumed suitable for factor analysis (CFA) if the p value for Bartlett's test of sphericity is less than 0.05, and secondly, if the value of MSA is greater than 0.05 (Hair, 2010).

Confirmatory Factor Analysis (CFA)

In the next stage, confirmatory factor analysis was employed since the EFA does not provide a definitive measurement test. In contrast to EFA, CFA requires a suitable definition of the underlying construct before a confirmatory test of the measurement theory (Legate et al., 2023). Generally, researchers are guided to modulate the constructs based on previous theory/literature, and test the validity of the conceptualized model given the sample data. CFA is most appropriate when it is applied to models with validated factor structures (Byrne, 2001a). Furthermore, CFA is suitable especially when applied to causal models, for example, indirect and causal effect estimations (James and Brett, 1984). Additionally, confirmatory factor analysis offers a broad collection of fit indices for theoretical model evaluation. Based on the above-mentioned merits CFA was employed to test the significance of the conceptualized model with the collected data set.

Moreover, the current study employed the "unmeasured latent factor method" suggested by (Podsakoff et al., 2003) to extract the common variance. Furthermore, by (Lowry et al., 2013), changes in standardized regression weights for measurement models (i.e., with and without common latent factor) were compared. A change greater than 0.200 in standard regression weight, that is, between a model with and without CLF, was deemed the cut-off point for the presence of common method bias.

Model Specification

Generally, SEM starts with model specification by developing the relations among the variables. Model specification was done based on the conceptualized research model, as shown in Figure 3.2.

Parameter Estimation

Once the model is specified, the subsequent step was estimation, which involves the specific estimation of free parameters form observed data. Generally, estimation techniques include instrumental variables (IV), un-weighted or ordinary least squares (ULS or OLS), two-stage least squares (TSLS), generalized least squares (GLS), and maximum likelihood (ML). Although all of the above-mentioned techniques are valid, ML was preferred over the others (Kline, 2005). The selection was based on the following characteristics of ML; first, ML is a free scale that helps with data transformation, such that estimates generated from transformed and untransformed variables are closely related. Secondly, ML shares the properties of minimum variance and un-bias. Third, ML appears robust against data non-normality, a property that is essential in the current study since the self-reported data is expected to yield slight non-normality. Forth, ML-based fit indices are more robust for model misspecification (Fornell and Larcker, 1981). In addition, researchers (Hill, argued that ML is a popular measurement technique when using SEM. In another study, Breckler (1990) reported that studies over the last 15 years with Likert scales have utilized the ML method for estimation. Based on the above reasons, ML-based fit indices were used in the present study. The ML fit estimation was measured as defined in the following equation (3):

$$ML = \ln|C| - \ln|S| + tr\left(SC^{-1}\right) - (p+q) \quad (3)$$

Where:

ln = natural logarithm;

C = actual covariance matrix;

S = covariance matrix implied by the model;

tr = trace (sum of the diagonal elements);

p = the number of observed variables in the model;

q = the discrepancy for the model; and

$|\ |$ = the determinant (index of generalised variance) of a matrix.

Interpretation of Parameter Estimates

Estimated parameters can be interpreted as either standardized or Unstandarized. Standardized estimates are the ones computed from standardized variables, whereas Unstandarized estimates are those computed from variables in their original units and researchers do not need to express variables as Z scores (normal deviates). A review of recent literature shows a strong preference for the use of Unstandarized estimates. This is also the case in the present study where Unstandarized estimates are used for estimation interpretation. Unstandarized estimates were selected for two reasons. First, interpretation yields more accurate results when used with the ML estimation method. Secondly, since the present study is aimed at measuring mediation effects, Unstandarized estimates were required to conduct the test (Byrne, 2001b).

Goodness-of-Fit Measures

The goodness-of-fit of a statistical model refers to how well it fits a set of observations. Table 3.10 depicts a summary of goodness-of-fit indices with their respective desirable criteria employed in the current study.

Absolute Fit Indices

Absolute fit indices indicate how well a priori model fits or reproduce the data. In order to evaluate SEM, absolute fit indices employed in the present study include the chi-squared test (χ^2), normed chi-square (NC), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI) and root mean square error of approximation (RMSEA). According to Hair et al. (2010), chi-square is the most basic absolute fit index and is measured as shown in equation 4:

$$\chi^2 = (N-1)(S-\Sigma_k) \tag{4}$$

Where:

N = the overall sample size;

S = the observed sample covariance matrix; and

$\sum_k$ = the SEM estimated covariance matrix.

In a study, (Byrne, 2001a) named χ^2 as a badness-of-fit index, since the greater the value, the worse the data fit to the model. In other words, a greater value of χ^2 relative to the degree of freedom depicts that the estimated and predicted metrics differ significantly. Although χ^2 is the most directly used absolute-fit index, there are some problems with it. For one, χ^2 is sensitive to multivariate normality distribution, especially under a small sample size. Then in complex models the observed χ^2 is always significant, even under a condition where goodness-of-fit is reasonably consistent with the data. Third, χ^2 is sensitive to sample size, whereby poor fit owing to small sample size may lead to a non-significant χ^2, whereas good fit due to a large sample size can lead to a significant χ^2. For these reasons a subjective evaluation was made to assess whether the non-significant χ^2 or significant χ^2 is actually that small to indicate model fit. In addition to χ^2, the value of NC (i.e., the ratio of χ^2 to the degree of freedom) was assessed, and an NC ratio value less than 5 was deemed to indicate reasonable model fit. In the next step, GFI and AGFI were assessed. GFI denotes the relative amount of variance and covariance in S predicted by the reproduced matrix $\sum$ (Byrne, 2001).

$$GFI_{ML} = 1 - \left[tr\left(\hat{\sum}^{-1} S - I\right)^2 / tr\left(\hat{\sum}^{-1} S\right)^2 \right]$$

Where:

tr = the trace (sum of the diagonal elements);

S = the observed sample covariance matrix;

I = identity matrix; and

$\hat{\sum}$ = the model-implied variance-covariance matrix.

In some studies proposed AGFI, adjusted for the degree of freedom (df) of a model concerning the number of variables. AGFI for the ML method was measured using the following equation (6):

$$AGFI_{ML} = 1 - \left[\left(k / df \right) \left(1 - GFI_{ML} \right) \right] \quad (6)$$

Where:

k = number of unique distinct values in observed sample covariance matrix; and

df = number of degrees of freedom in the model.

The values of GFI and AGFI can fall between 0 and 1, but greater values indicate a better fit. It was proposed that a model can be considered good if the values for GFI and AGFI are greater than 0.80 (Lowry et al., 2013). Similarly, recent researchers believe that GFI and AGFI values ranging between 0.80 and 0.90 indicate a good fit. Consequently, ML-based RMSEA was introduced, as RMSEA is arguably less sensitive to distribution and sample size (Hu and Bentler, 1998). In this study, ML-based RMSEA as shown in equation (7) was used:

$$RMSEA = \sqrt{\frac{\hat{\delta}_M}{df_M (N-1)}} \quad (7)$$

Where:

$\hat{\delta}_M$ = amount of approximation error;

df_M = the degree of freedom; and

N = the overall sample size.

Model Re-specification

Model re-specification refers to a process where researchers are required to modify the initial conceptualized model based on poor fit indicated by the fit indices. According to (Anderson & Gerbing, 1988), a model can be re-specified in four ways. For one, a factor can be related to a different factor; second, by deleting some indicators for the model; third, one indicator can be related to a number of factors; and forth, by using correlation measurement error. In order to assess the modified model (i.e., re-specified) researchers generally use modification indices (MI) as the guideline. The MI is a guideline for AMOS program users to add or delete links that actually deteriorate the model fit. However, (Anderson & Gerbing, 1988) considered that the re-specification decision should not only be based on statistical considerations; rather, it should always be aligned with theory and MI was employed in conjunction with well-established theoretical reasoning.

Test of Mediating Effects

The term mediation denotes a variable that develops a structural relationship between an independent (predictor) and dependent (outcome) variable (Baron & Kenny, 1986). However, a structural relationship between an independent, mediator and dependent variable may produce indirect effects (Babin et al., 2008). An indirect effect is the impact of a variable on an alternate that is intervened by an intervening variable in a model. According to (Hoyle, 1995) the indirect term is consistent with mediation, the only difference being that mediation comes from psychological literature, whereas indirect effect is a common term in sociology. Both regression and SEM analysis are used by researchers to test mediating effects since both strategies share the same logic. However, some (Baron & Kenny, 1986) view SEM as more efficient and less problematic.

Figures 3.4 and 3.5 describe the meaning of mediation through a three-variable causal path diagram. In Figure 3.4, path c represents a direct path from an independent to a dependent variable. In Figure 3.5, path a represents a direct path from an independent variable to the mediator; path b represents a direct path from the mediator to the dependent variable; and path c' represents a direct path from the independent variable to the dependent variable when a mediator is added to the model.

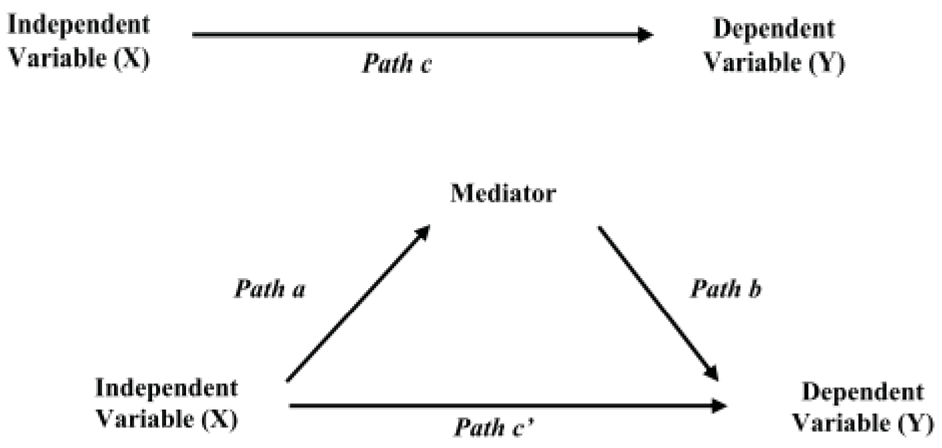

Figure 3.4**: Relationship between IV and DV without mediator**

Mediation testing requires the estimation of three regression equations (Baron & Kenny, 1986): first, the mediator is regressed on the independent variable to ascertain path a; second, the dependent variable is regressed on the independent variable in order to establish path c; and finally, the dependent variable is regressed on the independent and mediator simultaneously to establish path c'. Furthermore, if the three conditions should hold true in order to develop an argument for mediation, then: (1) the relationship between the independent variable and mediator should be significant, (2) the effect of the independent variable on the dependent variable should be significant, and (3) the effect of the mediator on the dependent variable must be significant (Baron and Kenny, 1986). If all the above conditions stand true, the effect of the independent variable on the dependent variable in equation (3) must be smaller than equation (2). The next step is to assess the significance of the mediating effect. A model can be classified as a fully mediating model if the relationship between the independent and dependent variables without a mediator is zero. A partial mediation model is one in which the relationship between the independent and dependent variable with a mediator (i.e., path c') is significant, but is small compared to when there is no mediator (path c), and still greater than zero. A no-`mediation model is one where the relationship between the independent and dependent variable remains significant and unchanged even after adding a mediator to the model.

Moreover researcher proposed that the difference between paths c' and c can also be examined by the product of paths a, and b. The rationale behind this is the difference between the two different paths (without mediator, path c, and with mediator and c') is equal to the product of paths a, and b only when it is divided by the respective standard error of the product of paths a, and b. This will yield a z-value of the mediating effect. An alpha level of 0.05 is deemed to indicate a significant effect if the z-value is greater than 1.96. Since the AMOS program lacks a standard error term of total direct or indirect effects, especially for ML estimation procedures, a hand-calculable statistical test proposed by (Baron & Kenny, 1986) was utilized as shown in equation (11):

$$\sqrt{b^2 S_a{}^2 + a^2 S_b{}^2 + S_a{}^2 S_b{}^2} \quad (11)$$

Where:

a = unstandardised regression coefficient of the path from the independent variable to the mediator;

b = unstandardised regression coefficient of the path from the mediator to the dependent variable;

S_a = standard error of a; and

S_b = standard error of b.

Therefore, in keeping to Kenny et al. (1998), the z-value was calculated through equation (12):

$$\frac{ab}{\sqrt{b^2 S_a{}^2 + a^2 S_b{}^2 + S_a{}^2 S_b{}^2}} \quad (12)$$

In addition, the indirect effects were also examined in this study by employing the bootstrapping technique suggested by Cronbach (1951). Bootstrapping is recommended when dealing with sample sizes that are too small, or there is a lack of power needed to estimate the significance of indirect effects. The procedure began by setting up the bootstrap. This study used 2000 bootstrap samples and bias-corrected confidence intervals (CIs) at 90% to determine the significance of the hypothesized mediation effects. In addition, direct effect, indirect effect, and total effect statistics were also utilized. If the model did not provide acceptable fit to the data, a similar model trimming process discussed earlier in the interaction process was employed.

Results & Discussion

Response Rate

Out of the final 1000 sample size, 430 surveys were received, representing a response rate of 43%. Out of these 430, 35 surveys were dropped because of missing data, leaving 395 useable surveys, representing a rate of 39.5%. A study analyzed 1607 studies published in 17 different referred academic journals between the years 2000 and 20005, and reported that the average response rate for studies that utilized data collected through a survey instrument at the organizational level was 34% (Baruch & Holtom, 2008). Thus, it appears the response rate of the current study is favorable considering the similar nature of research. Response facilitating techniques employed were timing (initial notification and follow-up), and technique (response-friendly, questionnaire, questionnaire structure and confidentiality of respondents).

Timing

Regarding timing, an introductory telephone call and email presenting the nature of the study were sent before distributing the self-reporting survey to respondents. Because it has been indicated that a preliminary notification is linked with a higher response rate. Secondly, following the general guideline of researchers, a follow-up reminder was made (telephone call) two weeks after the initial distribution.

Techniques

According to researchers, the response rate is highly influenced by the length of the questionnaire. To facilitate response, an attempt was made to make the questionnaire respondent-friendly by keeping the length of the survey short so it could be completed in 25 to 30 minutes. Second, the survey questionnaire was sent to respondents with college affiliation, including a cover letter explaining that the objective of the survey is a college research connection (National College of Business Administration & Economics). Third, the respondent's anonymity was also assured in order to improve the response rate (Jobber & O'Reilly, 1998). For this reason, respondents and their answers are kept anonymous in the present study. 350 of 1000 employees did not respond to any calls and 150 employees refused to participate. Moreover, 500 employees who were contacted agreed to participate in the survey and 400 employees returned useable surveys.

Table 4.1: Sample Response

Elements	Numbers
Total sample	1000
Employees who did not respond to any calls (n = 350) or refused to participate (n = 150).	500
Employees who agreed to participate never returned the survey.	80
Returned survey.	420
Useable survey.	400
Response rate.	40%

Respondent's Profile

The survey was conducted from November 2023 to January 2024. A total of 500 questionnaires were sent to those employees who agreed to participate in the study. Following the general guideline the observations with missing data were deleted, leaving a total of 400 useable questionnaires. Out of these 400, 20 questionnaires were found to be outliers and were deleted in accordance to the methods discussed in chapter 3. A total of 380 useable questionnaires were used for analysis, representing a net response rate of 76%. The profile of the respondents is shown in table 4.2.

Table 4.2: Respondent's Profile

Gender	**Frequency**	**Percent**
Male	238	62.6%
Female	142	37.4%
Total	**380**	**100%**
Age		
18-22 years old	158	41.6%
23-27 years old	197	51.8%
Above 28 years old	23	6.6%
Total	**380**	**100%**
Ethnicity		
Pakistani	380	100%
Total	**380**	**100%**
Duration of employment		
1-3 years	147	38.7%

3-5 years	192	50.5%
More than 5 years	41	10.8%
Total	**380**	**100%**
Industry sector		
Manufacturing	380	100%
Total	**380**	**100%**

The respondents comprised 238 (62.6%) male and 142 (37.4%) female. The age group distribution of the respondents is as follows: 41.6% are 18-22 years old, 51.8% are 23-27 years old, and the remaining 6.6% are above 28 years old. The ethnicity of respondents signifies 100% of Pakistani. The results also indicate that 100% of the sample respondents are from the manufacturing sector.

Measurement Model estimation

To measure reliability, we computed Cronbach's alpha and composite reliability (CR). CR and Cronbach alpha values for all theoretical constructs were considerably over the acceptable threshold of 0.70, according to Table 1 (Anderson & Gerbing, 1988). In this way, the results give proof of dependability. Both convergence and discrimination are considered legitimate. Convergent validity was tested using confirmatory factor analysis (CFA). All factor loadings should be more than 0.50 and statistically significant at the 0.01 level of significance. An extracted factor's average variance (AVE) value is considered legitimate if it is more than 0.50 (Hair et al., 2010). In Table 1, all factor loadings were more than 0.50 and all AVEs were greater than 0.50, suggesting convergence validity. Each factor is regarded as discriminant valid if the square root of its AVE is higher than its correlation coefficient with other factors (Fornell & Larcker, 1981). Because the square root of each variable's average value is larger than its correlation coefficient with other components, discriminant validity was also attained, as shown in Table 2. If an item is meant to measure one latent construct, but measures a distinct latent construct, it has discriminant validity. Inter-factor correlations were used to assess the discriminant validity of the model (Anderson & Gerbing, 1988). There is discriminant validity, as seen in Table 1. We utilised the Cronbach's coefficient, which is a well-used approach for measuring reliability in empirical literature, to evaluate dependability. Sources of value co-creation include knowledge exchange, interaction and equity (Table 3). There were substantial positive effects on dynamic brand experience from the source of value co-creation, as measured by the coefficient of determination (R2 = 0.182; F = 58.135; p 0.05). Dynamic brand experience is favorably influenced by value co-creation motivation (Table 4). There were statistically significant positive impacts of value co-creation motivation on dynamic brand experience (B = 11.458, F = 131.281, p 0.01; R2 = 0.330, F = 131.281, p 0.05).

A dynamic brand experience has a beneficial impact on consumer loyalty and trust (Table 5). In terms of consumer equity, the dynamic brand experience had statistically significant positive benefits (= 11.007; F = 121.164; p 0.05). Accordingly, the data (see Table 6) support H1, H2, and H3. Table 7 provides the findings of OLS regression studies to assess the moderating influence of E-WOM on the connection between dynamic brand experience and consumer equity. E-WOM, we postulated in H4, modifies the connection between dynamic brand experience and consumer equity in a favourable way. (B= 2.490; p 0.05) in the third step of the regression analysis, and it contributed significantly to the variance explained (R2 = 0.326, F = 44.150, p 0.05). Table 6 illustrates that the interaction term was found to be significant and positive. As a result, H4 is fully supported.

Table 2
Correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. KS	0.742 [a]																
2. Interaction	0.525**	0.800															
3. Equity	0.578**	0.452**	0.779														
4. SIN	0.150*	0.201**	0.198**	0.815													
5. HN	0.235**	0.256**	0.185**	0.578**	0.858												
6. EIN	0.128**	0.126*	0.055	0.380**	0.243**	0.859											
7. PIN	0.118	0.076	0.203**	0.423**	0.213**	0.244**	0.823										
8. TE	0.302**	0.326**	0.274**	0.399**	0.530**	0.218**	0.278**	0.846									
9. RE	0.234**	0.187**	0.206**	0.515**	0.450**	0.293**	0.268**	0.467**	0.854								
10. SE	0.228**	0.167**	0.192**	0.264**	0.341**	0.119	0.115	0.344**	0.309**	0.856							
11. AE	0.366**	0.262**	0.326**	0.321**	0.352**	0.245**	0.307**	0.521**	0.414**	0.520**	809						
12. BE	0.263**	0.277**	0.194**	0.383**	0.486**	0.228**	0.180**	0.560**	0.509**	0.533**	0.508**	824					
13. CE	0.330**	0.322**	0.227**	0.303**	0.360**	0.231**	0.308**	0.532**	0.456**	0.358**	0.473**	0.562**	0.837				
14. RE	0.290**	0.179**	0.264**	0.221**	0.293**	0.095	0.158**	0.358**	0.289**	0.430**	0.463**	0.449**	0.377**	0.827			
15. VE	0.237**	0.255**	0.188**	0.168**	0.223**	0.155*	0.067	0.250**	0.164**	0.234**	0.210**	0.327**	0.298**	0.357**	0.806		
16. BE	0.315**	0.238**	0.236**	0.230**	0.392**	0.121*	0.061	0.356**	0.258**	0.395**	0.294**	0.424**	0.346**	0.576**	0.480**	0.888	
17. E-WOM	0.286**	0.322**	0.185**	0.196**	0.282**	0.123*	0.229**	0.374**	0.273**	0.290**	0.289**	0.402**	0.514**	0.286**	0.214**	0.301**	0.822

Note: a Square root of AVE is on the diagonal.
** Correlation is significant at the 0.01 level (2-tailed)

Table 3
Hypotheses tests between source of value co-creation and dynamic brand experience.

Model	Dynamic brand experience $R^2 = 0.179$ / $F = 58.138$				
	Unstandardized Coefficients		Unstandardized Coefficients	T	P
	B	Std. Error	Beta		
(constant)	−5.184	0.682		−7.600	***
Source of value co-creation	1.526	0.200	0.423	7.625	***

Note: *p < 0.05, **p < 0.01, ***p < 0.001.

Table 4
Hypotheses tests between motivation of value co-creation and dynamic brand experience.

Model	Dynamic brand experience $R^2 = 0.330$ / $F = 131.281$				
	Unstandardized Coefficients		Unstandardized Coefficients	T	P
	B	Std. Error	Beta		
(constant)	−12.226	1.068		−11.445	***
Motivation of value co-creation	3.983	0.348	0.574	11.458	***

Note: *p < 0.05, **p < 0.01, ***p < 0.001

Table 5
Hypotheses tests between dynamic brand experience and customer equity.

Model	Customer equity $R^2 = 0.312$ / $F = 121.164$				
	Unstandardized Coefficients		Standardized Coefficients	T	P
	B	Std. Error	Beta		
(constant)	3.794	0.015		259.735	***
Dynamic brand experience	0.161	0.015	0.559	11.007	***

Note: *p < 0.05, **p < 0.01, ***p < 0.001.

In the process of producing value for businesses, consumers are becoming increasingly empowered and connected. As a result, more firms are shifting their attention from goods or services per se to customer experiences of their products (Lemon & Verhoef, 2016). A dynamic brand experience is created as a result of social network platforms, which enhance the creative form of this experience by adding the essence of phase and consistency. In the process of producing value for businesses, consumers are becoming increasingly empowered and connected. As a result, more firms are shifting their attention from goods or services per se to customer experiences of their products. A dynamic brand experience is created as a result of social network platforms, which enhance the creative form of this experience by adding the essence of phase and consistency.

Table 6
Hypotheses tests.

Structural paths	Standardized coefficient	t-values	Hypothesis test
Source of value co-creation → Dynamic brand experience	0.423***	7.625***	H1: Supported
Motivation of value co-creation → Dynamic brand experience	0.574***	11.458***	H2: Supported
Dynamic brand experience → Customer equity	0.559***	11.007***	H3: Supported

***$p < 0.001$; *$p < 0.05$.

Table 7
The results of verification of the moderating effect of the E-WOM.

Variables	Standardized coefficients		
	Model 1	Model 2	Model 3
Constant	11.965	5.443	−1.926
Dynamic brand experience	11.007	8.957	3.865
E-WOM		−1.464	−2.627
Dynamic brand experience * E-WOM			2.490*
F value	121.164	61.913	44.150
R^2	0.312	0.318	0.333

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Conclusion

Value co-creation and dynamic brand experience were favorably correlated in the first place, both in terms of their source and motive. By combining knowledge sharing, equity, and interactions, co-creation generates value that leads to the accumulation and construction of dynamic brand experiences. When customers and firms work together to develop new products, they engage in co-production behaviour. This co-production behaviour leads to social practice and brand experience for customers. The process of building a brand experience through interactive learning between a company and its customers is called value co-creation. A dynamic brand experience is a product of effective value co-creation efforts. There was also a favourable correlation found between dynamic brand experience and consumer equity. Affective experience, according to Gobe (2010), may capture consumer emotions, enabling consumers to develop and enter a specific kind of life, and encourage the formation of long-term brand connections.

Brand experience is phased and cumulative in the setting of social networking. A dynamic brand experience plays a crucial part in building client loyalty in today's marketplaces. As a result, marketers may increase customer loyalty by providing customers with the greatest dynamic experience. E-WOM plays a key role in regulating dynamic brand experience and consumer equity. Customers will be more convinced if the EWOM they receive is favourable and of good quality. As a result, the brand, which is strongly informed by future, existing, or past consumers, may better utilise people's changing brand experiences in customer equity. Therefore, marketers are continuously trying to influence consumers' views and actions toward items through altering E-WOM. Customer value creation is gaining academic and industrial attention at a time when customers have more widespread access to knowledge and resources on social network platforms, and may engage in the product innovation of companies to accomplish value co-creation through social networks. A lack of knowledge of the link between value co-creation and dynamic brand experience for increasing consumer equity and generating long-term profits has plagued past studies, though. A corporate marketing plan can benefit from this research on dynamic brand experiences based on value co-creation.

Despite the fact that dynamic brand experience and consumer equity are important theoretical ideas, there has been a dearth of study on the subject. Factors influencing dynamic brand experience, and how such experiences affect consumer equity, are emerging areas of study which require more development. It was the goal of this study to address that gap by proving experimentally that a dynamic brand experience driven by value co-creation on social networking platforms also contributes to the formation of social capital and has a positive impact on consumer loyalty. Results show that paying greater attention to dynamic brand experience in terms of value co-creation will help managers gain a better knowledge of consumer behaviour and encourage more rigorous study in this field. This study's focus was on the dynamic brand experience. This experience in the social networking environment is the result of all past experiences with a specific brand that have been accumulated through time. As a result of this brand experience, customers can have a more thorough understanding of the product and make more informed purchase decisions. Brand experience is dynamic in social networking, but existing research ignores this fact and does not examine this variable in terms of its phase or consistency. According to this survey, dynamic brand experience plays a crucial part when it comes to creating and maintaining client loyalty.

Limitations & Future Directions

The study includes several limitations, which provide potential for further research in the field of nutrition. First, due to the small number of observations, future research will require a comparison study with a larger sample across cultures and age groups. It also found that brand experience through social networks was very variable. In future study, the measuring instrument will need to be implemented with diverse antecedents and outcomes. This was due to the fact that the research of dynamic brand experience is still in its infancy. It was necessary to alter a section of a theoretical framework to arrive at the hypothesised link between variables in this investigation. We thus recommend more studies to enhance and deepen the theoretical framework of customer-driven brand experience.

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