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Original Paper

The Roles of Customer Engagement, Self-Efficacy, and Sensitivity to Privacy in Driving Customer Value in Digitalizing Services: A Moderated-Mediation Model

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Abstract

While customer engagement and self-efficacy in perceiving customer value have been scantily addressed, the interaction of sensitivity to privacy in digitalizing services remains underexplored. The study depends on self-determination and social exchange theories and examines a moderated-mediation research model using survey data from 326 consumers across China. The results show that the measurement and structural models of customer engagement have a positive and statistically significant relationship with self-efficacy and perceived customer value in adopting service digitalization behaviors. The findings also confirm the conditional mediating role of consumers' self-efficacy between customer engagement and customer value. Using the moderated analysis, consumers' sensitivity to privacy significantly dampens the links between customer engagement and self-efficacy (perceived customer value). It further suggested implications for theory, practices, and some limitations to step up the research scope in service digitalization.

Keywords

service digitalization, customer engagement, sensitivity to privacy, self-efficacy, perceived customer value

1. Introduction

More than ever, service digitalization is becoming a prominent servicescape, replacing physical marketing. Service automation is characterized by a blurry blending of technology-enabled digital and biological domains (Pradeep et al., 2019); consumer-led cocreation beyond the direct reach of service providers (McColl-Kennedy et al., 2017); and putting the effort, stress, and responsibility for service outcomes on the consumer (Anderson et al., 2016). So, it goes against the traditional view that services can't be replaced by machines (Autor & Dorn, 2013) and advances toward the servicescape of Artificial Intelligence (AI) that encourages engagement with customers (Huang & Rust, 2021), which leads to great service results. Consumers may have doubts or become hesitant about valuing Service Digitalization (SD); for example, consumers remain unwilling and uncertain to accept robot-based services (Deutsch et al., 2019); the diverse scope of how actor-context-system-outcome integrates (Helkkula et al., 2018) has raised the critical question of what intervenes in customer value. Service digitalization, therefore, demands a synergetic view of service touch points that provide a consumer with an opportunity to responsibly communicate and interact with service platforms.

Customer value is a key factor that affects process output, customer experience, and evaluating products and services. However, there isn't much research on how customer engagement, self-efficacy, and sensitivity to privacy affect customer value in adopting service behavior (Grewal et al., 2020; Hollebeek et al., 2020; Bieler et al., 2021). There is more knowledge about marketing concepts that focus on customer value. For example, the key challenges of service are to provide incremental and fair value (Williams et al., 2020); service providers try to anticipate service gaps and diagnose a problem to fix a system that keeps some consumers from seeing value (Boenigk et al., 2021).

However, service outcomes subject to co-creation and engagement have been subtle and sparse to date on the involvement of cognitive processes in service research (Bieler et al., 2021). Features of an inclusive servicescape, such as consumers' self-efficacy and engagement, may have contributed to perceived customer value. Besides, analyzing the servicescape from consumers' broader perspective (Xiao & Kumar, 2021; Huang et al., 2021) can identify service gaps or immense possibilities on how SD might facilitate achieving higher or lesser customer value. An innovative service landscape involves diverse actors, situations, contexts, and priorities that demand broadening our scope of understanding (Helkkula et al., 2018); blurred boundaries of service encounters (Harvey et al., 2020) impact service value. Specifically, the nature of Service Digitalization (SD) demands high participation of consumers (Ng et al., 2019), consumer-led cocreation (Sweeney et al., 2015), and active cognitive involvement of consumers (Bieler et al., 2021). Other research needs on digital tradeoffs on consumers' privacy concerns versus effectiveness in customization in the service environment (MSI, 2018) have been assumed to moderate with the proposed research model. Similarly, the active interaction of customer engagement in automated service is in its nascent stage and disparate in the research stream (Hollebeek et al., 2020); the

service platform has continually changed in the turbulent environment (Grewal et al., 2020). For example, the question of how consumers' privacy sensitivity may interact with service engagement and individual consumers' differences in adopting a new servicescape impacts valuing SD. Specifically, the current research is based on the gaps to enhance our understanding of to what extent customer engagement, self-efficacy, sensitivity to privacy, and under what conditions to realize the higher or lesser value of SD. The study has three theoretical and managerial implications. First, it examines the direct extent of relationships between customer engagement and both customer self-efficacy and value in response to research gaps and paradoxes (Hollebeek et al., 2020; Grewal et al., 2020; Bieler et al., 2021) that have left a theoretical void. Further, it reveals evidence of an indirect effect of consumer self-efficacy between perceived customer value and engagement in SD marketing research. Third, the research sheds light on the influence of consumers' sensitivity to privacy moderation between the study's constructs. Finally, it presents recommendations for practitioners' implications on service design and effectiveness from consumers' broader perspectives.

The remaining part of this article proceeds as follows: The study is organized as a first component to incorporate the theoretical foundation, literature review, hypotheses development, and research frame. Next, it discusses the study's methodology, which elaborates on procedures for data collection, measurement instruments, and sampling techniques. In the subsequent section, it presents the findings and discussions that follow with theoretical and managerial implications, as well as the study's limitations, as fertile ground for future research.

2. Theoretical Background

2.1 Theoretical Foundation

The theoretical basis of the study is the Self-Determination theory and Social Exchange theory, which are the ground rationale for opting for a theory as suggested by Wacker (1998). These justifications are to serve as a framework, a lens for theory development, and clarity to explain in a pragmatic world. Given these rationales, the following explanation focuses on SDT and SET, given the study's implications.

2.1.1 Self-Determination Theory (SDT)

The self-Determination Theory (SDT) is a well-known motivational theory because it has a significant impact on the level and caliber of motivation that a person's particular domain has when engaging in an activity (Ryan & Deci, 2017). It categorizes external motivation as an individual engaging to perform for a benefit or avoid punishment, while internal motivation is caused when he or she acts to gain value, importance, comfort, and interest as an attachment to his or her performing an activity. Both types of motivation exhibit a continuum; for instance, when a person has excess internal motivation, they demonstrate higher motivation than an externally motivated individual does. More specifically, the SDT implies that extrinsic motivation recognizes that a consumer performs an activity not for reasons to

satisfy others but for intrinsically motivated behavior that inherently shows self-interest or enjoyment in operating it. SDT scholars find it interesting that intrinsic motivation is what drives a person to do something even when they don't like it (Deci & Ryan, 1985). Intrinsic inclination helps with psychological growth, internalization, and wellbeing, but Ryan and Deci (2000) argue that individual differences or conditions can lead to counter-behaviors that can stop development, internalization, and wellbeing. Further, the SDT notes that an individual's growth, internalization, and wellbeing are subject to the person's basic psychological needs for autonomy, competence, and relatedness. The person's autonomy can demonstrate a consumer's sense of ownership, represented by psychological freedom, competence, which refers to the extent of mastery of skills, and relatedness, which encompasses senses of interconnectedness or networking to fulfill demands.

2.1.2 Social Exchange Theory (SET)

Social Exchange Theory (SET) comprises four constituents of an individual's social behavior: reinforcement tools, exchange, social relations, and reciprocity (Davlembayeva & Alamanos, 2022). First, the underpinning tools of reinforcement are the individuals' motivation to engage in social interaction. A rewarding relationship outcome originates from positive connotation while putting resources in place to enable the capability to own reward and inducing people to exchange relations (Emerson, 1976). Second, the exchange component refers to mechanisms of exchange postulating resource exchange based on cost-reward analysis (Blau, 2017; Cropanzano & Mitchell, 2005). Third, social exchange relations induce social structures and capital interactions on the parties' contingency of outcomes, forms of social entities embedded in norms, rules, information exchange, and obligations. Fourth, reciprocity mechanisms in social exchange create obligations between the parties (Molm, 1997; Cropanzano & Mitchell, 2005; Emerson, 1976), signifying interdependence, mutual and complementary arrangements, and negotiated rules that eventually become a breeding ground for trust, loyalty, and mutual commitment.

2.1.3 Literature Review and Hypothesis Development

Customer Engagement

Customer engagement has been a disputable concept among scholars. For instance, Harmeling et al. (2017, p. 312) view Customer Engagement (CE) as "motivate, empower, and measure customer contributions to marketing functions"; Hollebeek (2011, p. 6) defines "the level of a customer's motivational, brand-related, and context-dependent state of mind that is characterized by specific levels of cognitive, emotional, and behavioral activity in brand interactions". Regardless of the ongoing debate, CE in SD is likely to influence three key components of customer involvement in realizing services. One key element is customer interaction with the servicescape, which focuses on achieving needs. The second element of engagement in SD possibly involves the willingness of consumers to participate in co-creation responsibly when processing a service. The final element focuses on consumers' level of

motivation that is portrayed using active cognitive, affective, and behavioral engagement in operating a service platform per the specified service design.

Customer engagement has both behavioral and relational implications for service digitalization. Barari et al. (2021) posit that customer engagement, from a behavioral perspective, has both organic and promoted pathways. An organic path may show the extent of the relationship between SD, while aspects of promoted pathways signify a functional or experiential practice of a service platform or brand. In addition, it also entails a relationship component in satisfying the emotional attachment of service partners' alignment, either directly or indirectly, to impact marketing outcomes (Pansari & Kumar, 2017). Others view the marketing outcomes as subject to the extent of customer-firm touchpoint interaction (Kumar et al., 2019); the development of organic relationships over time (Palmatier et al., 2019); and the influence of customers' experience or functioning of the service touchpoints (Beckers et al., 2018). SD that possibly encourages high customer engagement can largely create a better attachment towards the servicescape, thus leading to perceived customer value. Drawing upon the SDT (Deci & Ryan, 1985; Ryan & Deci, 2000), internal and external clues of motivation predict consumers' behavioral intention when the SD can provide better possibilities for engagement. According to the underpinnings of SET (Blau, 2017; Cropanzano & Mitchell, 2005), customer engagement promotes social exchange and interaction to conceive higher customer value. Thus, the study postulates that

Hypothesis 1: There is a positive link between Customer Engagement (CE) and Perceived Self-Efficacy (PSE) in service digitalization.

Hypothesis 2: In service digitalization, Customer Engagement (CE) is positively related to Perceived Customer Value (PCV).

Consumer Self-Efficacy

In operating a service system, self-efficacy has been viewed differently, underscoring a similar concept. A consumer's confidence and mastery of specific activities or processes in a service system (Ellen et al., 1991; Maddux et al., 1982) is the capacity to operate SD. Ellen et al. (1991) described self-efficacy as a person's competence to perform a task or behavior; Mohar and Bitner (1995) view it as a level of energy put into a behavior; and Balau (2017) views self-efficacy as an individual's capabilities, a self-emotional state focused on improving one's development, performance, and quality of life.

Self-efficacy is consumers' beliefs about their capabilities to exercise at designated standards the performance of a service digitalization. Bandura (1994) believes that self-efficacy determines how people think, feel, get motivated, and behave, and yet, assurance of individual capability has remained a difficult task on issues of sustaining behavior. Consumers doubts about their capabilities can be a threat, and they may lose faith in operating SD. As a result, consumers may demonstrate less effort and commitment to learning a servicescape. Extant literature conjures on sources of efficacy, namely, mastery of experience, referring to a sense of efficacy; vicarious experience about creating and

strengthening self-belief; social persuasion, encompassing strengthening people's belief to succeed; and modifying self-belief, examining the situation of reducing stress and negative reactions (Bandura, 1997, 2006, 2012). Thus, this study anticipates self-efficacy to have an intervening role in adopting SD behavior with its operational definition of a consumer's motivation, readiness, and determination to operate a digitalized servicescape. According to SDT (Ryan & Deci, 2000), consumers' competence and internalization reinforce SD behavior, given that servicescape capabilities significantly influence service outcomes. Besides the SET (Molm, 1997; Emerson, 1976), social exchange relations and obligations induce interactions within the specified social structure that may underpin consumers to acquire skills to generate fruitful outcomes. Therefore, the study predicts that:

Hypothesis 3: Perceived Self-Efficacy (PSE) has a mediating effect between Customer Engagement (CE) and Perceived Customer Value (PCV).

Consumers' Sensitivity to Privacy

Consumers raise privacy tensions regarding the extent, when, and in what form their data will be exposed to others (Quach et al., 2022). Considering the conception of privacy tension, Hung and Wong (2009) categorized consumer privacy into three types: information, communication, and individual. Consumers have the right to regulate the access, use, and dissemination of privacy data, which can be a contentious issue with service providers. Next, communication privacy aims to protect personal messages and interactions, and finally, individual privacy involves personal space for intrusion, emotional manipulation, interference, and unsolicited marketing (Westin, 1967) that affect individual consumers' wellbeing.

Consumers' sensitivity to privacy includes a feeling of worry or fear that evokes protective action (Walker, 2016), the severity of privacy risks (Lwin et al., 2007), privacy-protecting strategies such as control over personal information, and permission for use (Walker, 2016). Consumers are continually calling for privacy protection, a remedy some consumers frequently invoke by switching service providers (Cisco, 2020), which can be a strategy to minimize privacy concerns. Remarkably, Quach et al. (2020) posed a question about how to create value in deploying customer data in SD.

Since modern life involves scattering millions of digital traces, data, and personal details (Brayne, 2021), consumers express their sensitivity to private data. As requirements for SD, consumers are required to submit personal data willingly, or the technology-enforced cookies collect data from individual consumers, and yet, it can be of use by intruders to inflict a consumer inconvenience or privacy breaches. A recent study by the Pew Research Center revealed that over 80% of Americans feel concerned about the lack of control over privacy data. Likewise, Ipsos (2021) found that only 3% believe they have control over the disclosure and removal of their data from online service platforms. Hence, to maintain healthy customer-provider relationships, it is interesting to assess the customer experience during SD. Specifically, excessive privacy concerns in SD weaken relationships between customer engagement and

consumers' self-efficacy or conceive higher customer value. According to the SDT (Deci & Ryan, 1985), consumers' concern for privacy falls around autonomy, relatedness, and competence as critical underpinning factors for responsible social exchange between service providers and customer relationships. Moreover, the SET (Molm, 1997) norm of reciprocity plays a critical role in a healthy social relationship on the grounds of trust, mutual commitment, and loyalty, urging specific obligational roles in privacy data collection, deployment, monitoring, and impact on the association with the service provider and customers.

Hypothesis 4: Sensitivity to Privacy (SPr) moderates the effect of Customer Engagement (CE) on Perceived Self-Efficacy (PSE), such that higher consumers' sensitivity to privacy weakens the relationship between customer engagement and self-efficacy.

Hypothesis 5: Sensitivity to Privacy (SPr) moderates the effect of Customer Engagement (CE) on Perceived Customer Value (PCV), such that higher consumers' sensitivity to privacy weakens the relationship between customer engagement and customer value.

3. Conceptual Framework

Inferring from the research gaps and literature review, a proposed research framework (Figure 1) to examine customer involvement and sensitivity to privacy affect customer value in service digitalization Consistent with cocreation conceptions and extant literature, it postulates direct causal links between customer engagement and perceived self-efficacy and customer value. Moreover, it predicts testing the mediating roles of self-efficacy between customer engagement and value in service digitalization. Finally, it attempts to explore the moderating effect of consumers' sensitivity to privacy influences on the study's constructs.

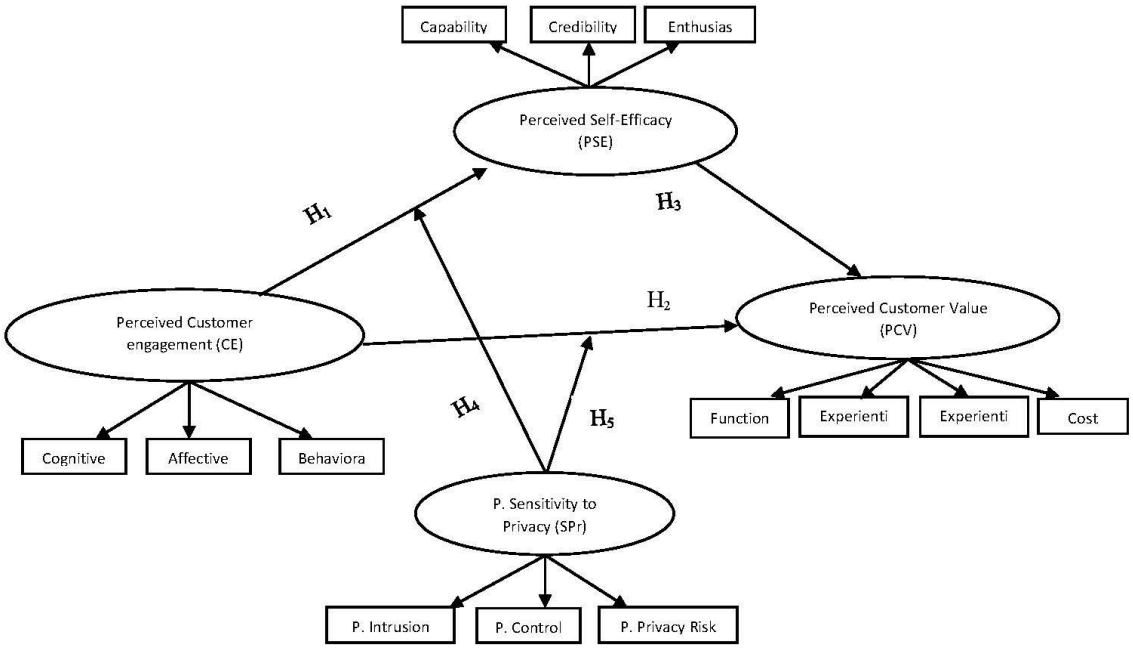

Figure 1. Proposed Research Frame

4. Methodology

4.1 Measurement and Questionnaire Development

In this study, the measurement tools were based on empirically validated scales from previous studies. The researcher measured all questionnaire items using a five-point Likert scale, designated by 1 as strongly disagreeing and 5 as strongly agreeing. Customer engagement had three indicators or measures—that is, cognitive, affective, and behavioral measures—from Boyd et al. (2019) operationalized into nine questionnaire items; three indicators (capabilities, credibility, and enthusiasm) for self-efficacy were adopted from Bandura (1986) tailored into nine items to suit the study's objectives. To measure consumers' sensitivity to privacy, measures of privacy intrusion, privacy risk, and privacy control were itemized into nine questionnaire elements by Xu et al. (2008). The researcher adopted measurements of perceived customer value from Smith & Colgate (2007): functional/instrumental, experiential/hedonic, symbolic/expressive, and cost/sacrifices. These measurements were slightly modified into the twelve questionnaire items. Initially, the questionnaire was pretested by three marketing researchers, which provided some enrichment. Next, it collected a pilot test of 30 sample questionnaires to confirm reliability and consistency across respondents (Malhorta, 2004). The reliability coefficient confirms above-0.8 standing high reliability (0.7-0.9) following Hilton et al.'s (2004) categorization.

4.2 Study Settings and Sample

The study targeted consumers across Chinese universities who have experienced digitalized services. Based on Henry's (1990) suggestion of a sampling technique that provides higher accuracy than a census, the study harvested a sampling frame of 7338 contact details of online consumers from six regional research panels, except for South China. Following Saunders et al.'s (2009) recommendation, a sample should have up-to-date and complete details. Using Cochran's (1977) and Saunders et al.'s (2009) guide on sample determination, the study required a sample of 462 consumers. The process is in line with the concept that, when a sampling frame is unavailable, the researchers can establish a sampling frame for the specific study, ensuring validity (Saunders et al., 2012) and undertaking marketing research at less cost from a population even when the sampling frame is indefinite (Kotler & Armestrong, 2015).

The study adopts multi-stage probability sampling, namely cluster sampling, which helps allocate proportionally to regions (the research panel), and random sampling techniques help pick each case. Taking into account what methodologists say, Jackob et al.'s (2005) collection of online contact addresses of the research target and Fredrick's (1941) probability sampling allow all cases to have a chance of being sampled. Coding of the sampling frame (letters representing a consumer's region and a sequential ID for each respondent) using the Microsoft Excel Rand function identified the potential respondents of the study. Next, it sent the survey questionnaire links using a consumer's online addresses because of feasibility and popular data collection (Malhotra & Briks, 2007); suitable data collection from the targeted respondents (Boyer et al., 2002). Table 1 presents the distribution of the sample per region and the response rate. The total of 326 respondents' data were collected out of 462 expected samples with a response rate of 71%, which exceeded Mendenhall et al.'s (2003) suggestion above 50% and Dellman's (2000) response range of 35-47% for online surveys.

Table 1. Distribution of Samples

	Frame	Sampled	Respondents
Northern China	743	47	33
North-East China	1621	102	72
North-West China	1283	81	57
South-Central China	1823	115	81
South-West China	1193	75	53
East China	675	43	30
South China			
	7338	462	326

5. Findings and Analyses

5.1 Demographics of Respondents

Table 2 presents the descriptive statistics of the survey's participants. Male respondents make up 56.1% and females make up 43.9% of the sample, similar to the UNESCO (2020) statistics that females in tertiary education account for 43%. The most sampled (51.8%) age band was 31-40, followed by 23% of 26-30. Similar to Mwencha et al. (2014) and Saleh and Bista (2017), the majority profile of the respondents' highest level of academic achievement reported a Master's degree of 55.8% and 35% for a Ph.D. Besides, according to the literature by Liou (1998), when a population differs substantially in age, ability, and other demographic factors, it is possible to break the equivalence assumptions. Furthermore, a run of multivariate regression estimates on the study's control variables shows an insignificant effect on customer value: sex (β = -0.003, t-value = -0.090, p-value = 0.928), age (β = -0.002, t-value = -0.664, p-value = 0.520), and the highest academic level of respondents (β = -0.035, t-value = -1.28, p-value = 0.200), implying free from bad control (Angrist & Pischke, 2009) that the control variables didn't have causal links with the study's dependent variable.

Table 2. Profile of Respondents

		Frequency	Percent
Sex	Male	183	56.1
	Female	143	43.9
	Total	326	100
Age Category	20 – 25	14	4.3
	26 – 30	75	23.0
	31 – 35	89	27.3
	36 – 40	80	24.5
	41 – 45	44	13.5
	46 – 50	22	6.7
	Above 51	2	.6
	Total	326	100
Highest Academic Level	Diploma	5	15
	First Degree	22	6.7
	Master's Degree	182	55.8
	PhD	114	35.0
	Post PhD	3	.9
	Total	326	100

5.2 Measurement Model Validation

In the procedure of verifying the measurement model, the study adopts Anderson and Gerbing's (1988) two-step approach: Confirmatory Factor Analysis (CFA) and reliability, convergent, and discriminant validity. The CFA was analyzed using SPSS-AMOS version 21 to ensure the validity of measurement models with the latent constructs, which established a goodness of fit of $\chi 2/df = 89.773/32 = 2.805$, RMR = 0.01, GFI = 0.942, AGFI = 0.900, NFI = 0.940, RFI = 0.916, CFI = 0.961, IFI =.961, TLI = 0.944, and RMSEA = 0.075, as suggested by Hu and Bentler (1999). Table 3 presents the standardized regression weights between measures and latent constructs that ensured the association had been well loaded. For instance, indicators of customer engagement range from standard regression estimates of $\beta = .72$ to 0.735, as CE1 to CE3 represent capability, credibility, and enthusiasm, respectively. The procedure for testing convergent validity consists of composite reliability and average variance extraction. The Composite Reliability (CR) coefficients are approaching 0.80, which exceeds Hair et al.'s (2011) standards of 0.70. Moreover, the four latent constructs and their respective measurements indicate the Average Variance of Extraction (AVE) above the 0.5 thresholds set by Fornell and Larcker (1981). MacCallum et al. (1993) and MacKenzie et al. (2005) suggested the diagnostics of reliability coefficient (α) should be above 0.7, and the tests carried out at 9 items of the questionnaire for the three latent variables and twelve items for PCV (bolded font) show above 0.8 and at measurement levels ranging from 0.758 to 0.791.

Table 3. Output Measurement Model (CFA, Convergent, and Reliability Coefficients)

			Stand. Reg. Weights	CR	AVE	α	α items level
CE1	<---	CE	0.718***	0.768	0.524	0.767	0.835
CE2	<---	CE	0.734***				
CE3	<---	CE	0.72***				
PSE1	<---	PSE	0.727***	0.784	0.548	0.786	0.826
PSE2	<---	PSE	0.715***				
PSE3	<---	PSE	0.778***				
PCV1	<---	PCV	0.671***	0.800	0.501	0.791	0.836
PCV2	<---	PCV	0.756***				
PCV3	<---	PCV	0.73***				
PCV4	<---	PCV	0.669***				
SPr1	<---	SPr	0.621***	0.77	0.534	0.758	0.805
SPr2	<---	SPr	0.873***				
SPr3	<---	SPr	0.673***				

Note: *** $p < 0.001$, CR = Composite Reliability, Standard Reg. Weights = Standardized Regression Weights, AVE = Average Variance Extracted, α = Reliability Coefficient

Table 4 presents discriminant validity test outputs using Pearson's correlation coefficients and square roots of AVE. The intercorrelation values are significant at a significance level of the p-value less than 0.01, where the highest and lowest values are 0.71 and 0.19, respectively. It is free from poor discriminant validity because the factors' correlations are less than 0.85 (Brown, 2006). It is in line with the intercorrelation of the constructs that fall less than unity to ensure discriminant validity (Bagozzi & Yi, 1991). The AVE square root for each construct should be greater than the correlation coefficients between any of the constructs involved to confirm discriminant validity (Fornell & Larcker, 1981). In addition, the Variance Inflation Factor (VIF) indicates a maximum value of 2.7, implying no problem of multicollinearity because the VIF value didn't fall above the threshold of 10 (Myers, 1990).

Table 4. Analyses of Discriminant Validity

	Correlations						
	Mean	Std. Deviation	VIF	PCV	CE	PSE	SPr
PCV	3.98	.42	2.527	0.707			
CE	3.98	.43	2.689	.664**	0.724		
PSE	4.00	.42	1.121	.712**	.732**	0.740	
SPr	3.96	.46	2.228	.186**	.325**	.211**	0.731

** Correlation is significant at the 0.01 level (2-tailed). N = 326

The diagonal bolded font values are square roots of AVE

5.3 Common Method Bias (CMV)

Since only one respondent completed the cross-sectional questionnaire, there may be a common method bias (Podsakoff et al., 2003). Hence, the study employed Harman's one-factor test; the study's variance of explanatory factor analysis for the prime factor shows 25.98%, signifying the study's dataset had no significant common method bias. In line with Williams et al.'s (1989) recommendation, the CMV should be less than the threshold of 40%.

5.4 Measurement Invariance

Byrne (2016) notes that measurement invariance focuses on one or more parameters to examine equivalence in both groups. The assessment of measurement invariance by gender in terms of factor loadings (measurement weights), structural variances and measurement errors, and goodness-of-fit indices is presented in Table 5, which shows relatively good fit models across both male and female

respondents. Specifically, the nested model of comparison for measurement invariance test confirms the models operate the same way in different subgroups (male or female) and shows the data's unbiasedness and suitability for making SEM decisions, similar to the studies carried out by Lakshman et al. (2020) and Tan and Pektas (2020).

Table 5. Nested Model Comparison-Measurement Invariance by Sex

Model	DF	CMIN	P	RMSEA	IFI	CFI	ΔNFI	ΔIFI	ΔRFI	ΔTLI
Unconstrained Model	118	264.291	.000	.062	.921	.920				
Measurement weights	23	71.864	.001	.063	.911	.910	.014	.015	.004	.005
Structural covariances	10	34.966	.000	.065	.897	.896	.018	.019	.007	.008
Measurement residuals	13	36.898	.000	.066	.883	.883	.019	.020	.003	.003

Where: Unconstrained Model: All parameters are freely predicted. Measurement weights: all factors are equated (constrained). Structural covariances: factor loading, variance, and covariance are constrained (equated). Measurement residuals: factor loading, variance, covariance, and error variance are equated (constrained).

5.5 Results of Hypotheses

The study employed the Hayes (2018) PROCESS procedure for SPSS version 3.5.3 to test the proposed moderated-mediation effect, Model 8, using the percentile bootstrap of 5000 samples at 95% Confidence Interval (CI) output because similar studies such as Khan et al. (2019), Akhtar et al. (2019), Keh and Sun (2018), and Edwards and Konold (2020) have adopted the procedure. Table 6 presents the output of the analysis that assumes statistical significance when the bootstrap (CI) is free from zero, and the model summary portrayed indicates statistical significance, implying the effect of the cluster and other variables in the model. Specifically, the statistical significance of the R^2 of 53.8% and 56.1% depicts that service digitalization roles of customer engagement as mediated by perceived self-efficacy (moderated by consumers' sensitivity to privacy) impact perceived customer value, confirming the research model. Results of the moderated-mediation analysis show direct, indirect, and interaction effects as per Edwards Konold's (2020) analysis techniques.

Direct Effect

The empirical result (Table 6) indicates consumers' engagement has a positive influence on perceived self-efficacy in service digitalization (a1 = $\beta_{CE \rightarrow PSE}$ = 0.91, t = 3.79, [0.44, 1.38], p <.001) and is statistically significant to support Hypothesis 1. The conditional direct total effect of CE → PCV, regression weight, misses statistical significance (p < 0.18), given that the model is incomplete on the relationship between CE and PCV because it deemphasizes the mediation process (Hayes, 2022), implying the relationship as a full mediation of hypothesis (Mathieu & Taylor, 2006), providing a clue to

the PSE role as a full mediator. Hence, model 8 programmed conditional PROCESS specifies two regression equations, one for the mediator and the dependent variable (Igartua & Hayes, 2021). It is recommended that the multilevel conditional process include the effect of the moderator (SPr) as a predictor (Hayes & Rockwood, 2020). Thus, the table shows -1SD (standard deviation), mean, and +1SD effect on direct relations of CE to PCV, where the average conditional direct effect represents $c'_{1} = \beta_{CE \rightarrow PCV} = 0.30$, t = 5.43, [0.19, 0.40], p <.001, where the CI is different from zero to support hypothesis 2.

Table 6. Moderated Mediated Results: Model 8 Process Output

	Mediator V (PSE)							**Dependent V (PCV)**					
		Coeff	SE	t	p	95% CI			Coeff	SE	t	p	95% CI	
						LLCI	ULCI						LLCI	ULCI
Constant		0.50	0.94	0.53	0.60	-1.36	2.35		3.33	0.91	3.67	0.00	1.55	5.11
Av_CE	a_1	0.91	0.24	3.79	0.00	0.44	1.38		-0.32	0.24	-1.35	0.18	-0.78	0.15
Int_1	a_3	-0.04	0.06	-0.73	0.47	-0.16	0.07	c'_3	0.16	0.06	2.72	0.01	0.04	0.27
Av_SPr	a_2	0.14	0.24	0.60	0.55	-0.32	0.61	c'_2	-0.63	0.23	-2.76	0.01	-1.08	-0.18
Av_PSE								b_1	0.48	0.05	9.06	0.00	0.38	0.59
Model S.		R^2 = 53.8%, MSE = .084, F(3,322) = 125, p = .000							R^2 = 56.1%, MSE = .078, F(4,321) = 102.7, p = .000					

Conditional Direct Effect of CE on PCV (c'_1)

				CI at 95%	
Effect	SE	t	p	LLCI	ULCI
0.23	0.06	3.64	0.00	0.10	0.35
0.30	0.06	5.43	0.00	0.19	0.41
0.37	0.06	6.20	0.00	0.25	0.49

Indirect Effect

Hypothesis 3: The analysis examined the mediating relationship between perceived self-efficacy, customer engagement, and perceived customer value. The empirical findings in Table 6 illustrate that the $\beta_{CE \rightarrow PSE}$ and $\beta_{PSE \rightarrow PCV}$ are significant as requirements for the predicted indirect relationship. As Preacher et al. (2007) posit that the unifying effect boils down to the conditional indirect effect of CE as mediated

with PSE affecting PCV, -1SD, mean, and +SD (Table 8) indicates bootstrapping indirect effects ($\beta_{CE \rightarrow PSE \rightarrow PCV} = 0.36$, bootSE =.06, CI = [.25 to.49], supporting full mediation hypothesis 3.

Table 7. Conditional Indirect Effects of CE on PCV (Av_CE -> Av_PSE -> Av_PCV)

Effect	BootSE	BootLLCI	BootULCI
0.368	0.0648	0.2498	0.5057
0.3583	0.0623	0.2474	0.4931
0.3485	0.063	0.2388	0.4851

Interaction Effect

Analyses of moderation were carried out to explore the effect of consumers' sensitivity to privacy that could influence relations between customer engagement and perceived self-efficacy (customer value). First, hypothesis 4 considers the potential moderation effects of consumers' sensitivity to privacy, indicating that the high-sensitivity context effect of customer engagement on perceived self-efficacy Table 6, Int_1, represents the interaction effect (CE*SPr), which appeared statistically insignificant (a1 = $\beta_{(CE*SPr)} = -0.04$, t-value = -0.073, and p = 0.47). However, the visualizing syntax of the conditional effect for probing the interaction effect (Figure 2) shows that when consumers have high sensitivity to privacy in a mean-centered manner (Aiken & West, 1991), it weakens the association between customer engagement and perceived self-efficacy in service digitalization to support the hypothesis. Specifically, the graph demonstrates that as consumers perceive higher rather than lower sensitivity to privacy in service, digitalization dampens the relationship between customer engagement and perceived self-efficacy.

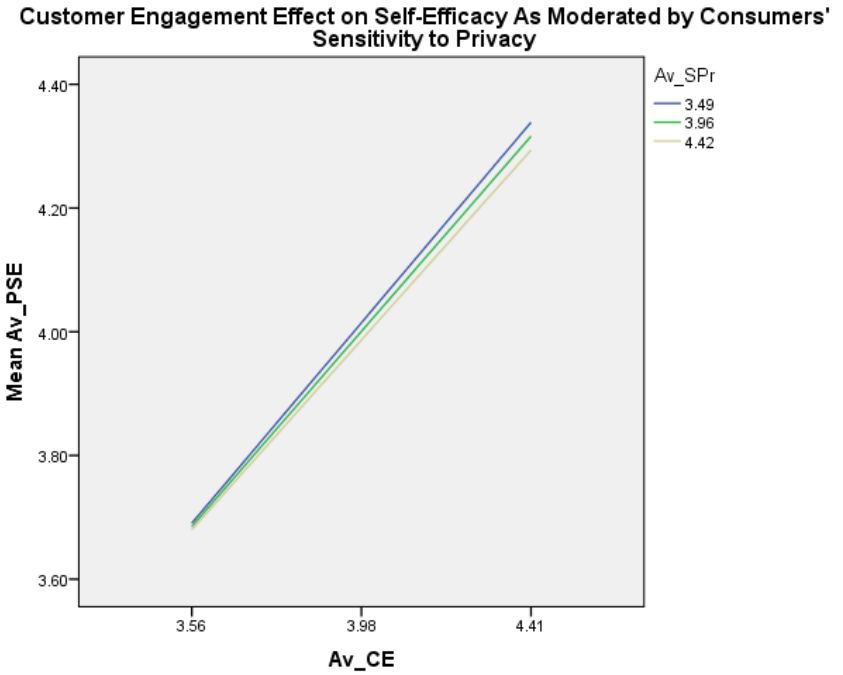

Figure 2. Customer Engagement Effect on Self-efficacy as Moderated by Consumers' Sensitivity to Privacy

Second, hypothesis 5 examines the moderation role of consumers' sensitivity to privacy, indicating that higher sensitivity to privacy influences the association of customer engagement and perceived customer value ($c'_3 = \beta_{(CE*SPr)} = 0.16$, t-value = 2.72, and p = 0.01) significantly during high versus low sensitivity concerns in support of the hypothesis. The moderation graphic visualization (Figure 3) shows that when consumers are more sensitive to privacy, it dampens the positive association between customer engagement and perceived customer value. In addition, the slope is steeper when sensitivity is high rather than low after plot intersection; however, it shows the reverse effect of interaction.

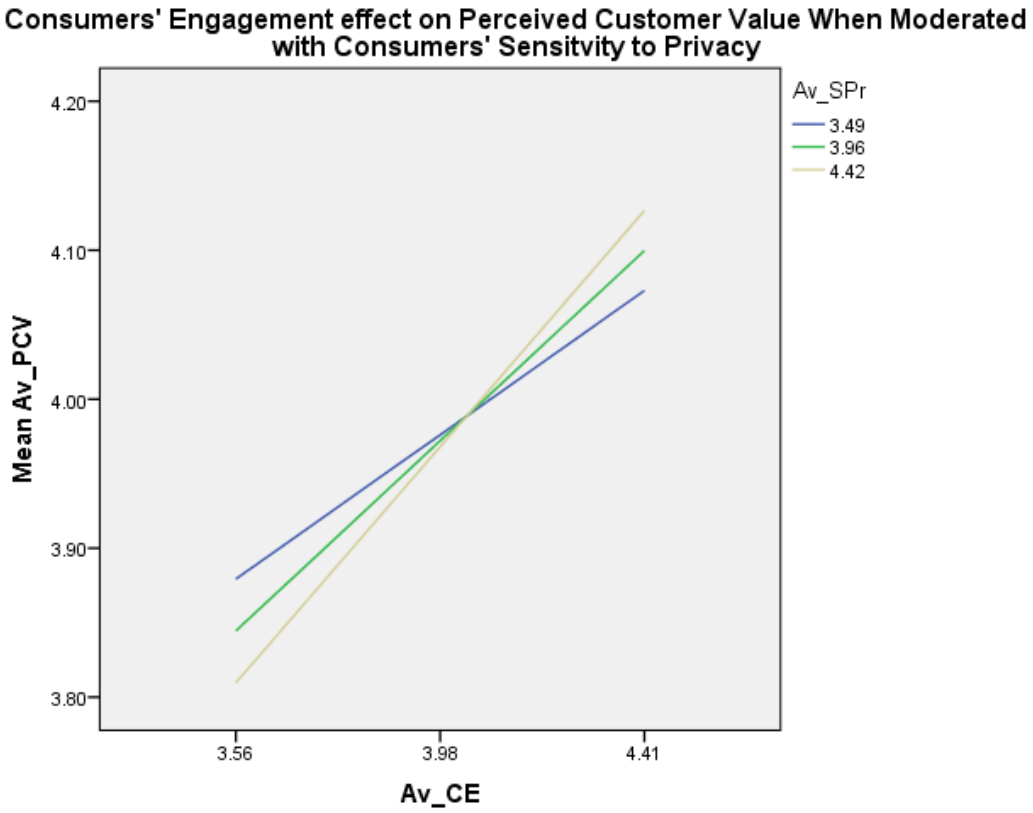

Figure 3. Customers' Engagement on Perceived Customer Value when Moderated with Consumers' Sensitivity to Privacy

Figure 4 is a graphic representation of the research model based on the ongoing development of multilevel moderated-mediated analysis (Zyphur et al., 2019; Edwards Konold, 2020).

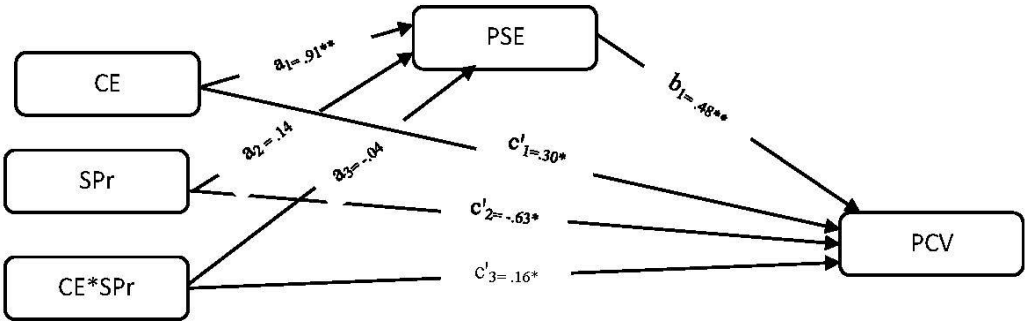

Figure 4. Moderated-Mediation Model of Interplays between Customer Engagement and Perceived Self-efficacy (Customer Value) Interacting with the Consumers' High Sensitivity to Privacy in Service Digitalization

6. Discussions, Implications, and Limitations

The results confirm the proposed hypotheses of customers' involvement as mediated by consumers' capacity and in the context of consumers' sensitivity to privacy in service digitalization. However, the extent and significance of a hypothesis warrant further discussion. The survey examines consumers' engagement in service digitalization, hypothesizing and validating the intervening role of consumers' self-efficacy in impacting perceived customer value. Besides, it tests the moderation effect of consumers' sensitivity to privacy on the constructs that established the interaction of customer engagement, and sensitivity to privacy affects perceived customer value after SPSS syntax for probing interaction (Hayes, 2018). It proved that consumers' empowerment in service digitalization is a critical element to improving perceived customer value as an impetus to theory on the intervening role of consumers' self-efficacy. The results suggest that while better customer engagement positively affects self-efficacy and customer value, excessive concern for privacy dampens the relationship between customer engagement and perceived self-efficacy (customer value). In particular, studies carried out on service marketing that assumed similar constructs seem worth discussing in processes of service digitalization (Dhagarra et al., 2020; Santini et al., 2020; Tam, 2019; Shoukat & Ramkissoon, 2022). Dhagarra et al. (2020), while examining the Technology Acceptance Model (TAM), argued that patient privacy concerns are a direct predictor of TAM behavior in health services. Unlike Dhagarra and colleagues' study, this study examined how and to what degree consumers' privacy concerns interact with the entire service digitalization; in cocreation, this is something that this study has ascertained.

The results confirmed hypotheses that customer engagement significantly contributes to service digitalization self-efficacy and perceived customer value. It confirmed empirically the propositions of customer engagement based on experience and then customer delight and revisit intention in tourism services (Shoukat & Ramkissoon, 2022). Besides, the findings of this study support the assertion of the meta-analysis that argued customer engagement in social media has substantial value for company performance, behavior intention, and positive word-of-mouth (Santini et al., 2020). Similar to this study, Mathieu and Taylor (2006) considered the intervening role of self-efficacy in organizational behavior and contended that self-efficacy has a positive mediating effect between normative information and performance in educational settings. Besides, Tam (2019) confirmed the moderating roles of self-efficacy in patient participation and satisfaction in health services. In contrast, this study explored the positive intervening role of service digitalization self-efficacy between customer engagement and perceived customer value. Given consumers as vital players in service co-creation, it is essential to widen the scope of the evidence-based moderated-mediation research model in service digitalization.

6.1 Research Implications

The research provides significant contributions on the theoretical front in establishing links between consumer behavioral responses and cocreation with regards to service digitalization. Additionally, the study also contributes to the extant literature on consumer behavior in digitalized services. Primarily, this study extended beyond self-reporting bias by confirming the use of measurement and structural models on consumers' behavior to perceive value in service digitalization. It also evidenced the role of customer engagement for self-efficacy in adopting service digitalization behavior, thus laying a foundation to widen our scope on the significance of cocreation in the context of digital support services. Few studies have addressed the roles of customer engagement and self-efficacy in service digitalization (Kipnis et al., 2022). This study attempts to unpack the interplay of customers' behavioral involvement that determines its extent for improved service outcomes.

The study also showed that perceived self-efficacy is a link between customer engagement and perceived value of service digitalization in response to marketing challenges to ensure incremental service value (Williams et al., 2020) and fixing service gaps to think of enhanced value (Boenigk et al., 2021) in service digitalization. The results of the study indicate that self-efficacy effectively intervenes between customer engagement and perceived customer value, impacting service digitalization behavior. Finally, the study explored the moderation effect of consumers' sensitivity to privacy on the study's constructs. Theoretically, existing literature is rather inadequate, demanding broadening the scope of service digitalization (Helkkula et al., 2018); blurred boundaries of the servicescape (Harvey et al., 2020); consumer involvement; and issues of consumers' wellbeing (Ng et al., 2019; Bieler et al., 2021). Although the extent varies, privacy concerns have been found to have a critical interaction effect on consumers' behavior with digitally supported services. Thus, the current study contributes toward understanding the role of privacy concerns in consumers' behavior when adopting digitalized services. Moreover, this study addresses the ongoing research paradox and gaps (Grewal et al., 2020; Hollebeek et al., 2020; Bieler et al., 2021) that established the measurement and structural relationship of the moderated-mediation model.

6.2 Managerial Implications

From managerial implications, the study presents the following key viewpoints: Firstly, in today's marketplace, digitalized services are engulfing the physical marketing that paves the way for service co-creation and customer involvement. Customers, therefore, are key players in service provision, and their engagement and operating skills in the servicescape play a paramount role in service outcomes. Secondly, technology is an enabler of service quality, particularly in consumers' eyes. Consumers' self-efficacy is the driving force behind adopting digitalized service behaviors when they feel engaged and perceive higher customer value. The study proved factors of engagement and self-efficacy have an effect on conceiving customer value and adopting service digitalization. Thirdly, consumers are

excessively concerned about their privacy, intrusions, risks, and associated control during interactions with digitalized services. Several consumers have concerns about the prevalence of privacy breaches that were found to have a negative influence on the perceived value of digital services. Practitioners must devise a strategically sound plan for assessing the privacy data process of data collection, usage, and monitoring to ensure consumers' confidence and wellbeing in adopting digital services. Last but not least, service marketing success depends on promoting efficient and effective digital services that empower consumers for higher value perceptions, and equally, managers are mandated to strive for greater adoption of service digitalization amongst consumers.

6.3 Limitations of the Study

The research has several limitations, and researchers are invited to extend its scope. The present research's main limitation is deploying the quantitative survey study that future researchers can complement using longitudinal, experimental, case, and qualitative studies for triangulation purposes. To further validate the present study, the proposed model may be examined in a different context—developing and developed countries and diverse cultures—and incorporate cross-cultural differences for generalizability. Additional opportunities for a study are to enrich the research model using constructs that may have an effect on service digitalization, including but not limited to perceived customization, customer delight, features of digital services, loyalty, customers' demographics, and social networks.

7. Conclusions

While service scholars have made fruitful efforts to address and unlock the mystery of knowledge gaps, there remains unaddressed research (Kipnis et al., 2022; Boenigk et al., 2021; Ng et al., 2019; Bieler et al., 2021; Dhagarra et al., 2020; Santini et al., 2020; Tam, 2019; Shoukat & Ramkissoon, 2022). The study attempted to unleash some potential gaps in advancing concepts on consumers' responses to service digitalization. Nonetheless, service digitalization is in its infancy stage, and we have further research endeavors to unlock the potential of service research.

Conflict of Interest

The author declares no conflict of interest. The author receives no funding for this research.

References

Aiken, L. S., &West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. Sage.

Akhtar, N., Sun, J., Chen, J., & Akhtar M. (2019). The role of attitude ambivalence in conflicting online hotel reviews. *Journal of Hospitality Marketing & Management*. DOI: 10.1080/19368623.2019.1650684

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411-423.

Anderson, L., & Ostrom, A. L. (2015). Transformative Service Research: Advancing Our Knowledge about Service and Wellbeing. *Journal of Service Research*, *18*(3) 243-249.

Anderson, L., Jelena, S., Josephine, G. J., Amy, L. O., Courtney, N. B., Sterling, A. B., Hilary, D., Martin, M., & Justine, M. R. (2016). Responsibility and Well-Being: Resource Integration under Responsibilization in Expert Services. *Journal of Public Policy and Marketing*, *35*(2), 262-279.

Angrist, J. D., & Pischke, J. S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Autor, D. H., & David, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, *103*(5), 1553-1597.

Bagozzi, R. P., Yi, Y., & Phillips, L. W. (1991). Assessing construct validity in organizational research. *Administrative Science Quarterly*, *36*(3), 421-458.

Balau, M. (2017). Self-efficacy and Individual Performance—Lessons from Marketing Research. The 12th Edition of the international conference. *Europe Integration, realties and prospects*, 255-264.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A. (1994). Self-efficacy. In V. S. Ramachaudran (Ed.), *Encyclopedia of human behavior* (Vol. 4, pp. 71-81). New York: Academic Press.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York: Freeman.

Bandura, A. (2006). Guide for constructing self-efficacy scales. In *Self-efficacy beliefs of adolescents*, 307-337.

Bandura, A. (2012). On the Functional Properties of Perceived Self-Efficacy Revisited. *Journal of Management*, *38*(1), 9-44.

Barari, M., Ross, M., Thaichon, S., & Surachartkumtonkun, J. (2021). A meta-analysis of customer engagement behavior. *International Journal of Consumer Studies*, *45*(4), 457-477.

Beckers, S. F. M., van Doorn, J., & Verhoef, P. C. (2018). Good, better, engaged? The effect of company-initiated customer engagement behavior on shareholder value. *Journal of the Academy of Marketing Science*, *46*(3), 366-383.

Bieler, M. Maas, P., Fiscer, L., Rietmann, N. (2021). Enabling Cocreation with Transformative Interventions: An Interdisciplinary Conceptualization of Consumer Boosting. *Journal of Service Research*, 1-19. DOI: 10.1177/10946705211003676

Blau, P. (2017). *Exchange and power in social life*. Abingdon: Routledge.

Boenigk, S., Aaron, A. K., Annika, B., Linda, A., Raymond P. F., and Sertan, K. (2021). Transformative Service Initiatives: Enabling Access and Overcoming Barriers for People Experiencing Vulnerability. *Journal of Service Research*, *24*(4) 542-562.

Boyd, D., Kannan, P., & Slotegraaf, R. (2019). Branded Apps and Their Impact on Firm Value: A Design Perspective. *Journal of Marketing Research*, *56*(1) 76-88.

Boyer, K., Olson, J., Calantone, R., & Jackson, E. (2002). Print versus electronic surveys: A comparison of two data collection methodologies. *Journal of Operations Management*, *20*, 357-373.

Brayne, S. (2021). *Predict and surveil: Data, discretion, and the future of policing*. New York, NY: Oxford University Press.

Brown, T. A. (2006). *Confirmatory factor analysis for applied research*. New York: The Guilford Press.

Byrne, B. M. (2016). *Structural equation modeling with AMOS: Basic concepts, applications, and programming*. Routledge.

Cisco. (2020). *Protecting data privacy to maintain digital trust: The importance of protecting data privacy during the pandemic and beyond, Cisco*. Retrieved from https://www.cisco.com/c/dam/en_us/about/doing_business/trust-center/docs/cybersecurity-series-2020-cps.pdf

Cochran, W. G. (1977). *Sampling Techniques*. New York: John Wiley.

Cropanzano, R., & Mitchell, M. S. (2005). Social exchange theory: An Interdisciplinary review. *Journal of Management*, *31*(6), 874-900.

Danatzis. I., Karpen, I., & Kleinaltenkamp, M. (2022). Actor Ecosystem Readiness: Understanding the Nature and Role of Human Abilities and Motivation in a Service Ecosystem. *Journal of Service Research*, *25*(2) 260-280.

Davlembayeva, D., & Alamanos, E. (2022). Social Exchange Theory: A review. In S. Papagiannidis (Ed), *Theory Hub Book*. http://open.ncl.ac.uk

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. New York: Plenum.

Dillman, D. A. (2000). *Mail and Internet Surveys, The Tailored Design Method*. New York: Wiley.

Deutsch, I., Hadas, E., Michal, P., Guy, H., & Oren, Z. (2019). Home Robotic Devices for Older Adults: Opportunities and Concerns. *Computers in Human Behavior*, *98*(9), 122-133.

Dhagarra, D., Goswami, M., & Kumar, G. (2020). Impact of Trust and Privacy Concerns on Technology Acceptance in Healthcare: An Indian Perspective. *International Journal of Medical Informatics, 141*, 104-164.

Dodds, W., & Monroe, K. (1985). The effect of brand and price information on subjective product evaluations. *Advances in Consumer Research, 12*(1), 85-90.

Edwards, K. D., & Konold, T. R. (2020). Moderated Mediation Analysis: A Review and Application to School Climate Research. *Practical Assessment, Research, and Evaluation*, 25(5). Retrieved from https://scholarworks.umass.edu/pare/vol25/iss1/5

Ellen, P., Wiener, J., & Cobb-Walgren, C. (1991). The role of perceived consumer effectiveness in motivating environmentally conscious behaviors. *Journal of Public Policy and Marketing*, *10*, 102-117.

Emerson, R. M. (1976). Social Exchange Theory. *Annual Review of Sociology*, *21*, 335-362.

Fredrick, F. S. (1941). Stratification in representative sampling. *Journal of Marketing*. https://doi.org/10.1177/002224294100600107

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Grewal, D., Noble, S., Roggeveen, A., & Nordfalt, J. (2020). The future of in-store technology. *J. of the Academy of Marketing Science*, *48*, 96-113.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed, a silver bullet. *Journal of Marketing Theory & Practice*, *19*(2), 139-152.

Harmeling, C. M., Moffett, J. W., Arnold, M. J., & Carlson, B. D. (2017). Toward a theory of customer engagement marketing. *Journal of the Academy of Marketing Science*, *45*(3), 312-335.

Harvey, J., Poorrezaei, M., Woodall, T., Nica-Avram, G., Smith, G., Ajiboye, T., Kholodova, K., & Zhu, K. (2020). The Smart Home: How Consumers Craft New Service Networks by Combining Heterogeneous Smart Domestic Products. *Journal of Service Research*, 1-23. DOI: 10.1177/1094670520929095

Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (3rd ed.). The Guilford Press.

Hayes, A. F., & Rockwood, N. J. (2020). Conditional process analysis: Concepts, computation, and advances in the modeling of the contingencies of mechanisms. *American Behavioral Scientist*, *64*(1), 19-54.

Hayes, A. (2018). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-based Approach*. New York: Guilford Press.

Helkkula, A., Kowalkowski, C., & Tronvoll, B. (2018). Archetypes of Service Innovation: Implications for Value Co-creation. *J. of Service Research*, *21*(3), 284-301.

Henry, G. T. (1990). *Practical Sampling*. Newbury Park: CA: Sage.

Hilton, S. C., Schau, C., & Olsen, J. A. (2004). Survey of attitudes toward statistics: Factor structure invariance by gender and by administration time. *Structural Equation Modeling: A Multidisciplinary Journal*, *11*, 92-109.

Hollebeek, L. D., Sportt D. E., & Brady, M. K. (2020). Rise of the Machines? Customer Engagement in Automated Service Interactions. *Journal of Service Research*, *24*(1), 3-8.

Hollebeek, L., Moira, C., & Keith, M. (2020). Demystifying Digital Cocreated Value: Social Presence Theory-Informed Framework and Propositions. *Recherche et Applications en Marketing, forthcoming*. DOI: 10.1177/2051570720961986

Hollebeek, L. (2011). Exploring customer brand engagement: Definition and themes. *Journal of Strategic Marketing*, *19*(7), 555-573.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives, Structural Equation Modeling. A Multidisciplinary Journal, *6*(1), 1-55.

Huang, M., Malthouse, E., Noble, S., & Wetzels, M. (2021). Moving Service Research Forward. *Journal of Service Research*, *24*(4), 459-461.

Huang, M.-H., & Roland, T. R. (2021). Engaged to a Robot? The Role of AI in Service. *Journal of Service Research*, *24*(1), 30-41.

Hung, H., & Wong, Y. H. (2009). Information transparency and digital privacy protection: Are they mutually exclusive in the provision of e-services? *Journal of Services Marketing*, *23*(3), 154-164.

Igartua, J. -J., & Hayes, A. F. (2021). Mediation, moderation, and conditional process analysis: Concepts, computations, and some common confusions. *The Spanish Journal of Psychology*, *24*, e49. Doi:10.1017/SJP.2021.46

Ipsos. (2021). Privacy by design: Exceeding customer expectations. Retrieved from https://www.thinkwithgoogle.com/_qs/documents/12055/Google_Privacy_Report_202-_v2.pdf

Jackob, N., Arens, J., & Zerback, T. (2005). *Sampling procedure, questionnaire design, online implementation, and survey response in a multi-national online journalist survey*. Paper presented at the Joint WAPOR/ISSC Conference: Conducting International Social Surveys. Retrieved from ciss.ris.org/uploadi/editor/1132070316WAPORPaper.pdf

Keh, H., & Sun, J. (2018). The Differential Effects of Online Peer Review and Expert Review on Service Evaluations: The Roles of Confidence and Information Convergence. *Journal of Service Research*. https://doi.org/10.1177/1094670518779456

Khan, M. S., Kadirov, D., Bardakci, A., Iftikhar, R., Baran, T., Kantar, M., & Madak, N. (2019). Social media analysis of anti-consumption in Turkey. *British Food Journal*, *121*(1), 22-34.

Kipnis, E., Mcleay, F., rimes, A., De Salle, S., Potter, S. (2022). Service Robots in Long-Term Care: A Consumer-Centric View. *Journal of Service Research*, *0*(0), 1-19.

Kotler, P., & Armstrong, G. (2015). *Principles of Marketing*. Pearson.

Kumar, A. K., Ilavarasan, V., Gupta, M. P., Janssen, M., & Kothari, R. (2019). Moving beyond Smart Cities: Digital Nations for Social Innovation & Sustainability. *Information Systems Frontiers*, *21*, 495-501.

Lakshman, C., Chi-Vo, L., & Ramaswami, A. (2020). Measurement invariance and nomological validity of the Attributional Complexity Scale: Evidence from Estonia, France, India, United States, and Vietnam. *Int. Journ. of Cross-Cultural Management*, *20*(1), 89-111.

Liou, M. (1998). Establishing score comparability in heterogeneous populations. *Statistica Sinica*, *8*, 669-690.

Lusch, R. F., & Vargo, S. L. (2014). *The Service-Dominant Logic of Marketing: Dialog, Debate, and Directions*. Abingdon: Routledge.

Lwin, M., Wirtz, J., & Williams, J. (2007). Consumer online privacy concerns and responses: A power-responsibility equilibrium perspective. *Journal of the Academy of Marketing Science*, *35*(1), 572-585.

MacCallum, R. C., Wegener, D. T., Uchino, B. N., & Fabrigar, L. R. (1993). The problem of equivalent models in applications of covariance structure models. *Psychological Bulletin*, *114*, 185-199.

MacKenzie, S. B., Podsakoff, P. M., & Jarvis, C. B. (2005). The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions. *Journal of Applied Psychology*, *90*(4), 710-730.

Maddux, J. E., & Stanley, M. A. (Eds.) (1986). Special issue on self-efficacy theory. *Journal of Social and Clinical Psychology*, *4*(Whole No.3).

Malhorta, N. K. (2004). Common method variance in Information Systems Research: A comparison of alternative approaches and analysis of past research. *Journal on management science*, *8*(1).

Malhotra, N., & Birks, D. (2007). Marketing research. *An applied approach*. Prentice Hall: London.

Mathieu, J., & Tylor, S. R. (2006). Clarifying conditions and decision points for mediational type inferences in Organizational Behavior. *Journal of Organizational Behavior J. Organiz. Behav.*, *27*, 1031-1056.

McColl-Kennedy, J. R., Suellen. J., Hogan, L. W., & Hannah, S. (2017). Cocreative Customer Practices: Effects of Health Care Customer Value Co-Creation Practices on Well-Being. *Journal of Business Research*, *70*, 55-66.

Mendenhall, M. E., Black, J. S., Jensen, R. J., & Gregersen, H. B. (2003). Seeing the elephant: Human resource management challenges in the age of globalization. *Organizational Dynamics*, *32*(3), 261-274.

Mohr, L. A., & Mary, J. B. (1995). The Role of Employee Effort in Satisfaction with Service Transactions. *Journal of Business Research*, *32*(3), 239-252.

Molm, L. D. (1997). *Coercive power in social exchange*.

MSI-Marketing Science Institute. (2016). *Research Priorities 2016-2018*. Cambridge, MA: Marketing Science Institute. Retrieved from http://www.msi.org/uploads/articles/MSI_RP16- 18.pdf

Mwencha, P., Muathe, S., & Thuo, J. (2014). Effects of Perceived Attributes, Perceived Risk, and Perceived Value on Usage of Online Retailing Services. *Journal of Management Research, 6*(2).

Myers, R. (1990). *Classical and modern regression with applications* (2nd ed.). Duxbury.

Ng, S. C., Jillian, C. S., & Carolin, P. (2019). Managing Customer Resource Endowments and Deficiencies for Value Cocreation: Complex Relational Services. *Journal of Service Research*, *22*(2), 156-172.

Palmatier, R. W., & Martin, K. D. (2019). Understanding and valuing customer data. In *The intelligent Marketer's guide to data privacy* (pp. 133-151). Palgrave Macmillan.

Pansari, A., & Kumar, V. (2017). Customer engagement: The construct, antecedents, and consequences. *Journal of the Academy of Marketing Science*, *45*(3), 294-311.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879-903.

Pradeep, A. K., Andrew, A., & Stan, S. (2019). *AI for Marketing and Product Innovation*. Wiley.

Preacher, K. J., Rucker, D. D., &Hayes, A. F. (2007). Assessing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research*, *42*, 185-227.

Quach, S., Thaichon, P., Martin, K., Weaven, S., Palmatier, R. (2022). Digital technologies: Tensions in privacy and data. *Journal of the Academy of Marketing Science*. https://doi.org/10.1007/s11747-022-00845-y

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*, 68-78.

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. New York: Guilford Publications.

Saleh, A., Bista, K. (2017). Examining Factors Impacting Online Survey Response Rates in Educational Research: Perceptions of Graduate Students. *Journal of Multi-Disciplinary Evaluation*, *13*, 29.

Santini, de O., F., Ladeira, W. J., Pinto, D. C., Herter, M. M., Sampaio, C. H., & Babin, B. (2020). Customer engagement in social media: A framework and meta-analysis. *Journal of the Academy of Marketing Science*, *48*(6), 1211-1228.

Saunders, M., Lewis, P. & Thornhill, A. (2012). *Research methods for business students* (6th ed.). England: Harlow Pearson Educational Limited.

Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for business students* (5th ed.). Pearson Education Limited.

Shoukat, M. H., & Ramkissoon, H. (2022). Customer delight, engagement, experience, value co-creation, place identity, and revisit intention: A new conceptual framework. *Journal of Hospitality Marketing & Management*. DOI: 10.1080/19368623.2022.2062692

Smith, J., & Colgate, M. (2007). Customer value creation: A practical framework. *Journal of Marketing Theory and Practice*, *15*(1), 7-23.

Sweeney, J. C., Tracey, S. D., & Janet, R. Mc.-K. (2015). Customer Effort in Value Cocreation Activities: Improving Quality of Life and Behavioral Intentions of Health Care Customers. *Journal of Service Research*, *18*(3), 318-335.

Tam, J. L. M. (2019). Examining the Role of Customer Self-Efficacy in Service Encounters. *Services Marketing Quarterly*. DOI: 10.1080/15332969.2019.1666534

Tan, Ş., & Pektaş, S. (2020). Examining the invariance of a measurement model by using the covariance structure approach. *International Journal of Contemporary Educational Research*, *7*(2), 27-39.

UNESCO. (2020). *Global Education Monitoring Report—Gender Report: A new generation: 25 years of efforts for gender equality in education*. Paris, UNESCO.

Wacker, J. (1998). A definition of theory: Research guidelines for different theory-building research methods in operations management. *Journal of Operations Management*, *16*(4), 361-385.

Walker, K. L. (2016). Surrendering information through the looking glass: Transparency, trust, and protection. *Journal of Public Policy & Marketing*, *35*(1), 144-158.

Westin, A. (1967). *Privacy and Freedom*. Atheneum, New York, NY.

Williams, Jerome D., David Lopez, Patrick Shafto, and Kyungwon Lee (2020). Technological Workforce and Its Impact on Algorithmic Justice in Politics. Customer Needs and Solutions,6(3–4), 84–91.

Williams, L. J., Cote, J. A., & Buckley, M. R. (1989). Lack of method variance in self-reported effect and perceptions at work: Reality or artifact? *Journal of Applied Psychology*, *74*, 462-468.

Li, X., & Kumar, V. (2021). Robotics for Customer Service: A Useful Complement or an Ultimate Substitute? *Journal of Service Research*, *24*(1), 9-29.

Xu, H., Dinev, T., Smith, H. J., & Hart, P. (2008). Examining the formation of an individual's privacy concerns: Toward an integrative view. *ICIS Proceedings*, 1-16.

Zeithaml, V. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *J. of Marketing*, *52*, 2-22.

Zeithaml, V. A., Verleye, K., Hatak, H., Koller, M., & Zauner A. (2020). Three Decades of Customer Value Research: Paradigmatic Roots and Future Research Avenues. *Journal of Service Research*, 1-24.

Zyphur, M. J., Zhang, Z., Preacher, K. J., & Bird, L. J. (2019). Moderated-mediation in multilevel structural equation models: Decomposing effects of race on math achievement within versus between high schools in the United States. In S. E. Humphrey, & J. M. LeBreton (Eds.), *The handbook of multilevel theory, measurement, and analysis* (pp. 473-494). American Psychological Association.