

Research Article

Using Artificial Intelligence to Predict Customer Satisfaction with E-Payment Systems during the COVID-19 Pandemic

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Received 11 February 2022; Revised 2 July 2022; Accepted 11 July 2022; Published 31 August 2022

Academic Editor: Miaochao Chen

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This study explores the impact of electronic payment systems on Saudi Arabia's customer satisfaction during the COVID-19 pandemic. Descriptive analytical approach of a sample of 1,025 people living in Saudi Arabia was used to answer the study questions and test its hypotheses. Then, a new hybrid fuzzy inference system (HyFIS) is proposed to predict customer satisfaction during COVID-19 pandemic. The proposed system contemplates customer resistance (CR), access to technology (AT), privacy (PV), costs (CT), and speed of efficiency (SE) as the input variables and customer satisfaction (CS) as the output variable. Various statistical tests are utilized to determine the efficiency of input variables in the obtained data. The statistical tests are multicollinearity tests, reliability and validity, ordinal least square (OLS), fixed effect, and random development. As a result, we can determine each input variable's direct and indirect impact on the CS. Under OLS, fixed effect, and unexpected effect, the SE, CT, PV, AT, and CR considerably impact EP. The EP has been shown to have substantial positive indirect implications. Under OLS, fixed effect, and random effect, the CT, PV, and CR are found to have a significant positive impact on CS. In addition, the AT has a substantial impact on CS in a fixed effect indirect effect. The results of HyFIS were compared to those of the adaptive network-based fuzzy inference system (ANFIS). The results reveal that HyFIS outperforms ANFIS in predicting CS based on the error criterion.

1. Introduction

All countries of the world have been negatively affected economically and healthily by the COVID-19 pandemic. Among these countries is Saudi Arabia, where Saudi Arabia recorded more than 751,000 confirmed cases with more than nine thousand deaths as of April 1, 2022 [1]. It was reported that the negative impact on Saudi Arabia's main gross domestic product (GDP) in 2020 was estimated to range between 4.8% and 9.8% compared to the baseline level, while the Saudi government's fiscal countermeasures resulted in a positive impact of 2.5% in real GDP [2]. Note that, more reliance has been placed on e-commerce (electronic commerce) and online banking services, as they are new ways of developing technology. It is worth noting that during the COVID-19 pandemic, global reliance on electronic payment expanded rapidly [3, 4]. According to a study from China banking and insurance news (2020), the number of transactions done via mobile payment, a sort of e-payment system, increased by 187% in the first quarter of 2020 in China compared to the previous year [5].

E-commerce has recently emerged as a connector between buyers and sellers or between producers and consumers. It allows for selling and buying different products based on transactions effectively made via various Internet services and performing EP through e-banking and mobile banking [6]. The banking industry is a significant industry that involves EP in different financial transactions. This allows for many transactions to occur easily and rapidly [7]. Consequently, EP is considered a significant pillar of e-commerce. Services of flexible payment are developed by banking systems such that these services can be exploited ubiquitously anytime (e.g., e-banking, mobile banking, and so on). Several clients are using these provided services with no restrictions on timing. In contrast, noncash payments are also practiced by them [8]. Furthermore, many e-commerce sites have been collaborating with banks to offer online payments with several security layers, particularly for global cross-currency transactions [9]. Additionally, banking services can support e-commerce when conducting different types of transactions. E-commerce should cooperate with banks to enhance the payment services within various online transactions to make it convenient for consumers when proceeding with their down payments, including several different choices of online payment [10].

The prominent theory in obtaining information is acquired from the Trust Theory Consumers' satisfaction can increasingly rely on reliability while making additional purchases as assumed by consumers' [11]. Trust is the major driving factor for customer loyalty [12]. In addition, EP systems should pay great attention to the security factor [13]. The protection and security systems within the EP system represent the primary focus for consumers in performing their transactions. When these two actions are applied, consumers can immediately conduct their payments. The entire risk should be avoided as they influence the lack of confidence in an institution. In addition, CS compares different services or goods purchased in line with the "customers" expectations. It causes a feeling of happiness because it matches their expectations [14]. The satisfaction of consumers possesses a significant impact on consumers' loyalty and repurchases of products and services [15].

Masudin et al. [16] examined the influence of the traceability system on Indonesia's food cold chain performance during the COVID-19 epidemic and defined the demands of cold food consumers in Indonesia regarding the traceability system. Indeed, the previous literature used OLS and structural equation models to predict CS. Al-Hashem et al [17] investigated the role of e-personalization and e-customization in achieving e-customer satisfaction in the case of COVID-19. Nasereddin et al. [18] studied the acceptance of mobile payments in Jordan, especially some factors that affect the acceptance of mobile payments in Jordan, such as PV, cost, and security. Neger and Uddin [19] investigated the factors affecting consumers' Internet shopping behavior during the COVID-19 pandemic in Bangladesh. This article measures variables such as price, product influence, payment, time-saving, security, psychological, and organizational factors that affect consumers' Internet shopping behavior during the COVID-19

pandemic. Hashem [20] discussed the factors that influenced change in customer behavior during the COVID-19 pandemic toward e-shopping. These factors include prices, necessity, payment method, frequencies, and availability of products. Note that, a variety of machine learning models have recently been applied for detecting COVID-19 pandemic [21-23]. The study by [24] aims to reveal the factors that impact EP acceptance based on different views derived from Saudi consumers. The link between the actual usage of an EP and the decision of an EP is afterward studied. Based on study's regression findings, the subjective standard, usage simplicity, gains, and self-efficiency influence Saudi consumers' EP systems' perceptions. Note that, there is no relevant research in the HyFIS and ANFIS model to predict CS based on the EP system's behavior. In this study, we have investigated the relationship between CR, AT, PV, CT, and SE with CS during COVID-19 by statistical approaches in Section 5. To do that, we created a questionnaire to measure the effects of e-payment systems and customer satisfaction in Saudi Arabia. Then, a new HyFIS and ANFIS are proposed to predict CS during COVID-19 pandemic. Note that, HyFIS method uses heuristic fuzzy logic rules and input-output fuzzy membership functions that can be optimally tuned from training examples by a hybrid learning scheme. In Section 2, we discussed the concept models for this study, whereas Section 3 discussed the research technique with details. The mathematical models we employed are described in Section 4, while the experimental results are reported in Section 5. Section 6 ended with the conclusion.

2. The Conceptual Model

The conceptual framework represents the assembled theories and the relationship between variables [25], describing the examined region. The structural model displays the relationship between the EP system on CS under COVID-19. Furthermore, it demonstrates the direct and indirect relationship between the independent variables (CR to change, AT, CT, SE, and PV concerns) on the dependent variable (EP customer satisfaction) at the significance level. This model is constructed on prior academics' theories published in peer-reviewed journals. Hypothesis testing aims to determine the impact of exogenous, endogenous, and moderating variables. If (P-value < chosen significance level), then we reject the null hypothesis [26]. The hypotheses were derived from the conceptual model described below in section 3.

(1) CS and performance have long been crucial factors in surviving and succeeding in today's competitive business [27]. It has received significant attention in the business literature due to its importance in determining customers' actions and purchasing behavior [28]. According to [29], customer satisfaction is a rating given by customers on how well an item or service meets their needs. The entrepreneur and stakeholders could use the impact of CS on e-money payment applications, such as convenience, time efficiency, and ease of operation, which are indicators to measure the success of CS [30]. According to [31], CS is a mental state in which clients compare their prepurchase expectations against their postpurchase impression of product performance. This evaluation is determined by the product's availability, the availability of information, and the demand for the product. Based on these three variables, customers will compare their expectations and views. Personnel service quality significantly impacts CS, while CS impacts customer loyalty. Technical service quality also significantly affects customer loyalty [32].

- (2) EP has attracted academicians and policymakers' attention as a significant new business model innovation in business and economic life [33]. Payment is a complex process with multiple stages and many parties involved. In the last few years, there has been significant growth in electronic payment services to make payments more efficient and convenient for consumers [16]. At the same time, technology has also impacted the scope of fraud in e-payment systems. One way to minimize this risk is by using biometric data like fingerprints or facial recognition as identification verification at each stage of processing payments. However, these systems are costly and cumbersome to run. The much-hyped "biometric ATM card" has failed to materialize due to the high cost of maintaining a network of biometric scanners at each ATM. The new idea of using a blockchain for payment seems simple enough and faster for the transaction [34]. Blockchain may increase product safety, security, and quality control. Adopting blockchain technology in supply chain operations and management may also minimize fraudulent counterfeiting, enhance sustainable supply chain management, and reduce the need for intermediaries. EP plays a role in making life easier for customers to solve their payment problems and increase their satisfaction. EP services refer to electronic payment instead of the traditional method in which the customers use cash on hand in the specified place. EP does not require more expenses, time, effort, and specific place than a traditional payment. The benefits of EP include its convenience, ease of use, quick transaction times, speedier payment, and simplicity of the payment transaction to increase CS [35].
- (3) CR refers to the customer's unwillingness to switch from conventional paying bills to electronic. CR was thought to be one of the critical reasons for the failure/success of innovations on the market [36]. Companies must understand CR and the variables that contribute to it to be more efficient in enhancing productivity, competitiveness, and profitability [37]. According to [38], this study was about consumers who are resistant to changing their way of paying their bills or replacing the traditional approach that relies on paper and factors that influence customers' attitudes about EP.

- (4) AT refers to a customer's ability to access technologies and use them. According to [39], AT and PV play an essential role in the EP. Social media may be a marketing strategy that allows users to connect, consume, collaborate, and achieve business-end goals [40]. Furthermore, one of the advantages of using social media as a communication platform is the ease of two-way contact between a company and its stakeholders. Followers' belief in influencers' sponsored postings is influenced by the informational value of influencer-generated material and the influencer's trustworthiness, attractiveness, and similarity to the followers [41]. Financial technology availability, accessibility, simplicity of use and performance, transaction costs, and service security positively and significantly impact bank client satisfaction [42].
- (5) PV determines the dangers of utilizing personal information and financial information online. [43] stated that customer service, trust issues, learning, and PV are some of the variables influencing EP. Security and PV are two of the many variables that are significant solid elements of satisfaction toward Fintech mobile payment, which is a component of EP systems [18, 44].
- (6) CT refers to customers willing to pay a low service charge to buy services and products [45] studied the effects of electronic banking services on client satisfaction using survey questions given to 175 Jordanians. The results show that the impact of these characteristics (convenience, cost, simplicity of use, personalization and customization, and security) on client satisfaction in the banking industry is favorable. Because the privacy indicator is linked with the other variables, it is removed from the model. Only PV has been found not to influence client satisfaction.
- (7) SE refers to customers unwilling to wait any longer than they have to for service or to buy the product. In our constantly evolving digital society, the options expanding every day, customers are more willing than ever to take their business elsewhere if they do not get what they want when they want it. According to [28], consumer satisfaction or dissatisfaction with electronic banking services results from constant assessment and monitoring. It is the most robust criterion for evaluating the bank's services. Customer satisfaction assessment assists the bank in enriching and adjusting the electronic banking services given in terms of convenience, flexibility, and SE, as well as the low CT of services.

3. Research Methodology

3.1. The Methodology of This Work Is Summarized as Follows

 In this study, we created a questionnaire to measure the effects of e-payment systems and customer satisfaction in Saudi Arabia. Figure 1 shows the selected



FIGURE 1: Research structural model. H01: There is no effect of the EP system on CS under COVID-19 at the level of significance ($\alpha \le 0.05$). H011: There is no effect of CR on CS under COVID-19 at the level of significance ($\alpha \le 0.05$). H012: There is no effect of AT on CS under COVID-19 at the level of significance ($\alpha \le 0.05$). H₀₁₃: There is no effect of PV concerns on CS under COVID-19 at the level of significance ($\alpha \le 0.05$). H₀₁₄: There is no effect of CT concerns on CS under COVID-19 at the level of significance ($\alpha \le 0.05$). H₀₁₄: There is no effect of CT concerns on CS under COVID-19 at the level of significance ($\alpha \le 0.05$). H₀₁₅: There is no effect of SE on CS under COVID-19 at the level of significance ($\alpha \le 0.05$).

elements, where the ingredients are chosen based on some statistical tests. These tests are multicollinearity tests showing reliability and validity, OLS, fixed effect, and random effect. The direct and indirect relationship of independent factors (CR to change, AT, CT, SE, and PV concerns) on the dependent variable (EP customer satisfaction) is described in Figure 1 [46]. The study examined these factors via the following hypothesis tests. The primary null hypothesis is H_{01} (there is no effect of the EP system on CS under COVID-19 at the significance level of less than 5%). The sub-null hypotheses are H011, H012, H013, H014, and H015.

- (2) We proposed new forecasting artificial neural network models using the HyFIS and ANFIS systems. The models are used to predict customer satisfaction with e-payment systems during the COVID-19 pandemic in Saudi Arabia.
- (3) The results of the proposed models are compared based on some of the statistical error tests.

4. Mathematical Models

4.1. Multiple Regression Models. A statistical approach that can be used to analyze the relationship between a single dependent variable and independent variables is multiple regression. The multiple regression analysis is used for the independent variables known to predict the single dependent value by their values. The weights are weighed for each predictor value, which denotes their relative contribution to the prediction.

$$X_i = \alpha + \sum_{i=1}^n \beta_i X_i + \varepsilon_i, \tag{1}$$

where Y_i are the dependent variables of the *i*-the observations and X_i , i = 1, 2, ..., n are the independent variables. The β_i , i = 1, 2, ..., n are the coefficients of independent variables, α is constant, and ε_i represents unobserved variable (error).

The direct and indirect effects examined in this section use three different approaches: the ordinary least square (OLS), the fixed effects, and the random effects. In statistics, OLS is a kind of linear least squares method for estimating the unknown parameters in a linear regression model. In addition, OLS selects the parameters of a linear function of a set of explanatory variables according to the principle of least square: minimizing the sum of the squares of the differences between the observed dependent variable in the specified dataset and those predicted by the linear function of the independent variable. The OLS estimator is consistent when the regressors are exogenous. When the errors have finite variances, the OLS method provides minimum-variance mean-unbiased estimate under the Gauss–Markov theorem.

The fixed effect is typically used in regression, assuming the independent variable is fixed. The random effects model is called a variance component model. Contrary to the fixed effects model, in the random effects model, the individualspecific effect is a random variable that is uncorrelated with the explanatory variables [47].

4.2. ANFIS Model. The ANFIS consists of both fuzzy logic and an artificial neural network. For ANFIS training, neural network learning algorithms will use [48]. Two processes, the forward and the backward step, consist of the "ANFIS" learning algorithm. The forward process goes via the five layers [49]. The fuzzy inference system under consideration should have two inputs (*x* and *y*) and one output (*z*) to simplify the explanations. A standard rule set of base fuzzy if-then rules for the first order of the Sugeno fuzzy model can be expressed as follows: if *x* is A_1 and *y* is B_1 , then $f_1 = p_1x + q_1y + r_1$; here, *p*, *r*, and *q* are linear output parameters. The "ANFIS" architecture with two inputs and one output is shown in Figure 2 [48, 49].

4.2.1. Layer 1. Every node *i* in this layer is a square node with a node function.

$$O_{1,i} = \mu_{Ai}(x) \text{ for, } i = 1, 2, 3,$$

$$O_{1,i} = \mu_{Bi-3}(y) \text{ for } i = 4, 5, 6,$$
(2)

where *x* and *y* are inputs to node *i*, and *A_i* and *B_i* are linguistic labels for inputs. In other words, $O_{1,i}$ is the membership function of *A_i* and *B_i*. Typically, $\mu_{Ai}(x)$ and $\mu_{Bi}(y)$ are selected to be bell-shaped with a maximum of 1 and minimum of 0, such as $\mu_{Ai}(x)$, $\mu_{Bi-3}(y) = \exp[-(x_i - c_i)^2/a_i]$, where the set of the parameter is a_i , c_i . These parameters are referred to as premise parameters in this layer. Indeed, using the Gaussian function as the shape of the membership function,



FIGURE 2: ANFIS architecture of two inputs and one output with four rules.

the fuzzification process transforms crisp into linguistic values.

4.2.2. Layer 2. Each node in this layer is a circle node labeled Π that multiplies the incoming signals and sends out the product. For example,

$$O_{2,i} = w_i = \mu_{Ai}(x) \cdot \mu_{Bi-3}(y), \quad i = 1, 2, 3, \dots, 9.$$
 (3)

Each node output describes the firing strength of a rule. The inference stage uses this layer's t-norm operator (the AND operator).

4.2.3. Layer 3. Each node in this layer is a circle node called N. The *i*th node measures the ratio of the *i*th rules firing strength to the sum of all rule's firing strengths:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{(w_1 + w_2 + \ldots + w_9)}, \quad i = 1, 2, 3, \ldots, 9.$$
 (4)

In short, the ratio of the strengths of the rules is calculated in this layer.

4.2.4. Layer 4. Each *i* node in this layer is a square node with a node function

$$O_{4,i} = \overline{w}_i \cdot f_i = w_i \cdot (p_i x + q_i y + r_i), \quad i = 1, 2, 3, \dots, 9,$$
(5)

where w_i is the output of layer three and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as consequent parameters. In short, the parameters for the resulting parts are evaluated in this layer.

4.2.5. Layer 5. A circle node called \sum is the single node in this layer that calculates the overall output as the summation of all incoming signals:

$$O_{5,i} = \text{overall output} = \sum_{i} \overline{w}_{i} \cdot f_{i} = \frac{\sum_{i} w_{i} \cdot f_{i}}{\sum_{i} w_{i}}.$$
 (6)

Indeed, the overall output as the sum of all incoming signals is determined in this layer. The backward step is a database estimation method consisting of the membership function parameters in the antecedent part and the linear equation coefficients in the consequent domain. Since the Gaussian function is used as the membership function in this process, two parameters of this function are optimized: mean and variance. The least squares method is employed to perform the parameter learning in this step.

Fuzzy inference systems (FIS) can solve regression problems in several domains. These systems utilize the fuzzy logic that maps input data to output data. A set of if-then fuzzy rules is generated for the input data during the mapping's fuzzification process. A membership function converts the inputs into normalized values and creates. The fuzzy if-then rules aim to perform pattern identification and decision support which leads to help in solving real-world problems. The FIS converts

Variables	Categories	Frequency	Percentage	Cumulative percentage
	Male	470	47.8	47.8
Gender	Female	513	52.2	100
	Total	983	100	
	<30	540	54.9	54.9
	30-40	351	35.7	90.6
Age	41-50	68	6.9	97.6
	>50	24	2.4	100
	Total	983	100	
	Postgraduate	192	19.5	19.5
Education	Bachelor	648	65.9	85.5
Education	Others	143	14.5	100
	Total	983	100	
Work	Manager	82	8.3	8.3
	Employee	426	43.3	51.7
	Student	398	40.5	92.2
	Unemployed	77	7.8	100
	Total	983	100	

TABLE 1: Sample profile.

the fuzzy sets into output values. These paradigms are efficient tools used in several scientific and engineering applications (e.g., forecasting) where these paradigms are developed to handle many environmental variables [50]. The hybrid neural fuzzy inference system (HyFIS), which was proposed by Kim and Kasabov [51], is a paradigm based on the FIS with the advantage of merging both fuzzy concepts with artificial neural networks (ANNs) [52] and, therefore, optimizing the learning process. The HyFIS improves on the FIS by using heuristic fuzzy logic rules and input-output fuzzy membership functions that are customized using a hybrid learning method that consists of two steps: rule generation and rule tuning [51]. When the errors have finite variances, the OLS approach yields minimum-variance mean-unbiased estimation. The HyFIS is being applied in different areas and used as a basis for developing other systems due to its capacity in enabling the neural network to learn fast and more accurately.

5. Experimental Results

5.1. Population and Sampling. This study has followed a questionnaire survey approach and extension of historical empirical studies consisting of CR, AT, PV, CT, SE, EP, and CS. The questionnaire contains two parts: the first part presents the demographic profile of the respondents, and the other part presents the study variable items depending on a 5-point Likert scale starting from (1) for "strongly disagree" to (5) for "strongly agree."

In the beginning, the pilot study was conducted to enhance the quality of the questionnaire. The 30 questionnaires were sent by e-mail to study the population, to make sure that respondents from the clear population understood the paragraphs of the questionnaire. A total of 23 questionnaires were collected, yielding a response rate of 77 percent, a reasonable response rate. Furthermore, the respondents within the pilot study were given some minor corrections to improve the quality of the questionnaire. This study's dataset consists of persons who lived in Saudi Arabia during COVID-19. A total

TABLE 2: Descriptive statistics of variables.

Variables	Ν	Mean	SD
CS	983	4.102	0.645
EP	983	4.495	0.468
CR	983	3.952	0.727
AT	983	4.333	0.622
PV	983	3.751	0.786
СТ	983	4.128	0.708
SE	983	4.248	0.632

TABLE 3: Correlation coefficients.

	CS	EP	CR	At	PV	СТ	SE
CS	1	0.509	0.528	0.581	0.213	0.318	0.68
EP		1	0.568	0.626	0.487	0.616	0.506
CR			1	0.498	0.275	0.337	0.47
AT				1	0.281	0.353	0.493
PV					1	0.47	0.184
CT						1	0.307
SE							1

TABLE 4: Exploratory factor analysis.

	Items	α	CR*	AVE
CS	8	0.908	0.927	0.616
EP	5	0.751	0.923	0.572
CR	4	0.709	0.839	0.567
AT	5	0.840	0.889	0.618
PV	5	0.771	0.844	0.525
CT	5	0.807	0.866	0.570
SE	4	0.831	0.890	0.671

AVE: average variance extracted, CR*: composite reliability, α : Cronbach's alpha coefficient.

of 983 out of 1025 questionnaires were used in the study. In this study, 96 percent of respondents were adopted. Forty-two questionnaires are also eliminated, such as partial replies or missing values. As a result, sample size plays a critical role in evaluating and explaining findings.

5.2. Descriptive Statistics. Table 1 shows the sample's demographic information. This table presents the respondent's profile for the present research. The percentage of respondents' gender is 47.8% male and 52.2% female. In addition, 54.9% of respondents are aged less than 30 years old, 35.7% are between 30 and 40 years old, and 9.3% are above 40 years old. The table also shows that a bachelor's degree percentage is 65.9%, and a postgraduate degree is 19.5%. The profile table explains that managers are 8.3% of respondents, employees are 43.3%, students are 40.5%, and unemployees are 7.8%.

Table 2 shows all research variables' mean and standard deviation (SD). The comparison indicates that EP has the highest mean and the lowest SD values.

5.3. Selecting Variables. In this section, the selected variables are based on a multicollinearity test depending on the correlation coefficients and variables' indirect and direct



FIGURE 3: Assumptions for OLS regression.

effects on ordinary least squares (OLS), fixed effect, and random effect.

The correlation coefficients are reported in Table 3. There is a strong correlation between variables if the absolute value of the correlation coefficient is equal and greater than 50%. Still, there is a weak correlation if the total value of the correlation coefficient is less than 50%. It shows a strong positive correlation coefficient between the dependent variable (CS) and other variables except PV and CT. It is important to note a strong positive correlation between the mediate variable (EP) and other variables excluding PV. Furthermore, there is a weak correlation between CR, AT, PV, CT, and SE. Indeed, there is no multicollinearity between these variables.

Table 4 shows the results of exploratory factor analysis (EFA) for reliability and validity items in the questionnaire. The results illustrate that the CS has the highest number of items, where Cronbach's alpha (α) is 0.908, composite reliability (CR*) equals 0.927, and average variance extracted (AVE) equals 0.616. In addition, the EP has five items, with α being 0.751, CR* equals 0.923, and AVE equals 0.572. Furthermore, the CR has four items where α equals 0.609, CR* equals 0.839, and AVE equals 0.567. Moreover, the AT has five items, where α is 0.840, CR^{*} equals 0.889, and AVE equals 0.618. Next, the PV has five items where α is 0.771, CR* equals 0.844, and AVE equals 0.525. Also, the CT has five items where α is 0.807, CR^{*} equals 0.866, and AVE equals 0.570. Furthermore, the SE has four items, where α is 0.831, CR* equals 0.890, and AVE equals 0.671. In terms of validity and reliability, the values of factor loadings are

acceptable because all of them are above. Furthermore, the results indicate that AVE results are above .50 while CR results are above .70, and alpha coefficients are no less than 0.7.

The first plot in Figure 3, "residuals vs. fitted," is useful for evaluating linearity and homoscedasticity: if the residuals (points on the plot) are primarily spread around the zero line, linearity is present. Homoscedasticity refers to the absence of a clear pattern in the residuals. This is also referred to as a residual distribution. The second plot, often known as the QQ-plot, is used to evaluate the assumption of normality: the closer the residual points are to the dotted 45degree line, the more likely the normality assumption is satisfied. The third plot is crucial for testing the hypothesis of homoscedasticity.

The last plot, often known as residuals vs. leverage plot, is a form of diagnostic graphic that identifies influential observations in a regression model. Each observation from the dataset is represented as a single point within the plot. The x-axis represents each point's leverage, while the y-axis represents each point's standardized residual. The degree to which the coefficients in the regression model would differ is referred to as leverage. Observations with high leverage influence the coefficients in the regression model. If we eliminate these observations, the model's coefficients will change significantly. The standardized difference between predicted and actual values is referred to as the residual. Any location in this plot that is outside of Cook's distance (the red dashed lines) is considered an important observation.

Effecte	Don war	Indep. var.	OLS			Fixed effect			Random effect		
Effects	Dep. var.		В	S.E	t-stat	В	S.E	Ζ	В	S.E	Z
		Intercept	1.380	0.078	17.74***	0.115	0.020	5.637***	1.347	0.077	17.522***
		SE	0.082	0.014	5.861***	0.119	0.022	5.509***	0.089	0.014	6.449***
		CT	0.135	0.015	8.895***	0.158	0.028	5.621***	0.131	0.015	8.802***
	EP	PV	0.230	0.018	12.65***	0.274	0.024	11.58***	0.221	0.018	12.245***
		AT	0.210	0.016	12.98***	0.132	0.023	5.669***	0.221	0.016	13.917***
Indiract		CR	0.097	0.017	5.572***	0.115	0.020	5.637***	0.101	0.017	6.034***
manect		R-square	0.639	0.731	0.714						
		F-stat.	346.5***	204.6***	1845.7***						
		Intercept	0.945	0.171	5.518***				0.945	0.171	5.518***
	CS	EP	0.702	0.038	18.54^{***}	0.630	0.065	9.764***	0.702	0.038	18.540***
		R-square	0.260	0.201	0.260						
		F-stat.	343.7***	95.3***	343.7***						
		Intercept	0.253	0.118	2.138***				0.253	0.118	2.138***
		SE	-0.009	0.021	-0.408	-0.054	0.037	-1.471	-0.009	0.021	-0.408
		CT	0.157	0.023	6.818***	0.175	0.039	4.523***	0.157	0.023	6.818***
Direct	CS	PV	0.261	0.028	9.471***	0.260	0.050	5.169***	0.261	0.028	9.471***
		AT	0.031	0.025	1.265	0.081	0.042	1.919*	0.031	0.025	1.265
		CR	0.471	0.026	17.85***	0.514	0.042	12.32***	0.471	0.026	17.850***
		R-square	0.562	0.563	0.562						
		F-stat.	250.5***	96.9***	1252.4***						

TABLE 5: The OLS, fixed effect, and random effect.

Signif. codes: "***" 0.01 "***" 0.05 "*" 0.1.

In our model, there are not any influential points. In the end, the least squares estimation is significantly based on previous assumptions.

Table 5 explains the indirect and direct effect of independent variables (SE, CT, PV, AT, and CR) on the dependent variable (CS) based on OLS, fixed effect, and random effect. In the OLS-indirect effect, the independent variables (SE, CT, PV, AT, and CR) have positive effect $(B_{SE} = 0.082, B_{CT} = 0.135, B_{PV} = 0.230, B_{AT} = 0.210, and$ $B_{CR} = 0.097$) on mediate variable (EP) with significant level less than 1%. The R-square equals 64%, and the F-stat is significant at 1%. So, we reject the null hypothesis (H₀₁₁, H₀₁₂, H₀₁₃, and H₀₁₄) at a significant level of 1%. Furthermore, the EP has a positive effect $(B_{EP} = 0.082)$ with a significance level of less than 1%. The R-square equals 26%, and F-stat is significant at 1%. So, we reject null hypothesis H_{01} at a significant level of 1%. In the fixed-indirect effect, the independent variables (SE, CT, PV, AT, and CR) have positive effect $(B_{SE} = 0.119, B_{CT} = 0.158, B_{PV} = 0.274,$ $B_{AT} = 0.132$, and $B_{CR} = 0.115$) on mediate variable (EP) with significant level less than 1%. The R-square equals 73%, and F-stat is significant at 1%. So, we reject the null hypothesis $(H_{011}, H_{012}, H_{013}, and H_{014})$ at a significant level of 1%. Furthermore, the EP has a positive effect ($B_{EP} = 0.63$) with a significance level of less than 1%. The R-square equals 20%, and F-stat is significant at 1%. So, we reject null hypothesis H_{01} at a significant level of 1%. In random-indirect effect, the independent variables (SE, CT, PV, AT, and CR) have positive effect $(B_{SE} = 0.089, B_{CT} = 0.131, B_{PV} = 0.221,$ $B_{AT} = 0.221$, and $B_{CR} = 0.101$) on mediate variable (EP) with significant level less than 1%. The R-square equals 71%, and F-stat is significant at 1%. So, we reject the null hypothesis (H₀₁₁, H₀₁₂, H₀₁₃, and H₀₁₄) at a significant level of 1%. Furthermore, the EP has a positive effect ($B_{EP} = 0.702$) with a significance level of less than 1%. The R-square equals 26%, and F-stat is significant at 1%. So, we reject null hypothesis H₀₁ at a significant level of 1%.

Table 5 illustrates the direct effect. In OLS-direct effect, the CT, PV, and CR have significant positive direct effect $(B_{CT} = 0.157, B_{PV} = 0.261, and B_{CR} = 0.471)$ on CS at 1% significant level. So, we reject the null hypothesis (H₀₁₁, H₀₁₃, and H_{014}) at a significant level of 1%. However, SE and AT do not have a significant direct effect on CS. So, we accept the null hypothesis (H_{012} and H_{015}) at a significant level of 5%. The R-square equals 56%, and F-stat is significant at 1%. In fixed-direct effect, the CT, PV, and CR have significant positive direct effect ($B_{CT} = 0.175$, $B_{PV} = 0.260$, and $B_{CR} = 0.514$) on CS at 1% significant level. So, we reject the null hypothesis (H_{011} , H_{013} , and H_{014}) at a significant level of 1%. Moreover, the AT has a significant positive direct effect $(B_{AT} = 0.081)$ on CS at a 10% significant level. In other words, we reject null hypothesis H_{012} at a significant level of 10%. However, the SE does not directly affect CS at a significant level of 5%. The R-square equals 56%, and F-stat is significant at 1%. In random-direct effect, the CT, PV, and CR have significant positive direct effect ($B_{CT} = 0.157$, $B_{PV} = 0.261$, and $B_{CR} = 0.471$) on CS at 1% significant level. So, we reject the null hypothesis $(H_{011}, H_{013}, and H_{014})$ at a significant level of 1%. However, SE and AT do not have a significant direct effect on CS. So, we accept the null hypothesis (H₀₁₂ and H₀₁₅) at a significant level of 5%. The R-square equals 56%, and F-stat is significant at 1%.

Improving the customer's ability to get AT will increase the customer's willingness to switch from the conventional

TABLE 6: ANFIS and HyFIS for predicting 10% of CS.

Tests	Maan	Independ	Independent <i>t</i> -test with original CS			Error criteria compared with original CS		
	Mean	T-test	Df	Sig.	ME	MPE	MAPE	
ANFIS	5	-12.405	95	<2.2e-16	0.7435	19.8823	19.8823	
HyFIS	3.903	2.770	144.64	0.00634	0.3539	8.2118	19.7814	
Original CS	4.257							

method of paying bills to the electronic method based on the effect of AT on EP in OLS method. Furthermore, the enhancing PV to use personal information and financial information in pay bills online will increase from the customer's willingness to EP as mentioned in OLS. Moreover, improving competitive CT to buy services or product online will contribute for the customer's willingness to EP. The policymaker in government and private organizations should also get attention on CR because it affects around ($\beta = 10\%$) on EP and ($\beta = 47\%$) direct on CS. In addition, the reducing waiting time to have online service or product (SE) will give indicator to increase customer's willingness to EP.

5.4. Prediction Results. In this section, the dataset is split into 90% (886 respondents) for training and 10% (98 respondents) for test prediction. After that, the five independent variables (SE, CT, PV, AT, and CR) were investigated to predict CS based on the adaptive ANFIS and HyFIS models with fifty iterations and the step size 0.01. Table 6 shows the predicting 10% of CS based on ANFIS and HyFIS. The predicting ANFIS and HyFIS are compared in mean with the original CS in this table. Independent t-test showed differences in means between ANFIS and original CS based on a significant level of less than 5% (reject H0: there are no differences in a mean between ANFIS and original CS). Also, there is a difference in means between HyFIS and original CS based on a significant level of less than 5% (reject H0: there is no difference in a mean between HyFIS and original CS). Indeed, the mean of HyFIS is closer to the original CS than ANFIS [48, 51].

However, the predicting ANFIS and HyFIS are compared in error criteria with original CS in this table also. The mean error (ME), the mean percentage error (MPE), and the mean absolute percentage error (MAPE) for predicting ANFIS with original CS are 0.7435, 19.882, and 19.882, respectively. Furthermore, the ME, MPE, and MAPE for predicting HyFIS with original CS are 0.354, 8.212, and 19.781, respectively. Indeed, the HyFIS is better than ANFIS in predicting CS for 10% of the dataset based on ME, MPE, and MAPE.

Table 6 shows the independent *t*-test, also referred to as the two *t*-test samples, the independent *t*-test samples, or the *t*-test of the student, is an inferential statistical test that tests if, in two unrelated groups (original CS and predicting CS), there is a statistically significant difference between the means. The null hypothesis of the independent *t*-test is $(H_0: \mu_1 = \mu_2)$ and alternative hypothesis $(H_0: \mu_1 \neq \mu_2)$, where μ_1 is the mean of group one (original CS) and μ_2 is mean of group two (predicting CS). We reject the null hypothesis because the significant level is less than 5%. 5.5. Managerial Implication. This section consists of the analysis results and managerial implications for enhancing the predicted CS with the EP system. Managerial implications for enhancing business policies are expected to contribute to management policies. This study asks governments and private institutions to take the indicator results to improve their service performance. Our recommendations can be summarized as follows:

- Improving the customer's ability to get AT will increase the customer's willingness to switch from the conventional method of paying bills to the electronic method approximately (β = 21%), as mentioned in OLS in Table 5. Moreover, this result is consistent with [39] the important role of AT in enhancing EP. Furthermore, the increase in EP will increase (β = 70%) CS, as mentioned too in OLS in Table 5. These results are also consistent with [42], who said that financial technology availability has a significant positive effect on CS.
- (2) Enhancing security and trust (PV) to use personal information and financial information to pay bills online will increase approximately ($\beta = 23\%$) the customer's willingness to EP, as mentioned in OLS in Table 5. Moreover, the strong significant effect of PV on EP consists of [44]. Furthermore, the PV affects approximately ($\beta = 26\%$) CS as the direct effect that is also mentioned in OLS in Table 5.
- (3) Improving competitive CT to buy services or products online will contribute about ($\beta = 13.5\%$) to the customer's willingness to EP. In addition, the reduced CT online will increase ($\beta = 15\%$) CS directly, as mentioned in Table 5. This result is consistent with [45], who said that CT has an effect on client satisfaction in Jordanian banks. The policymaker in government and private organizations should also pay attention to CR because it affects around ($\beta = 10\%$) EP and ($\beta = 47\%$) direct CS, as mentioned in Table 5. The CR effect on customers' attitudes about EP is consistent with [38]. Furthermore, reducing the waiting time to have an online service or product (SE) will give an indicator to increase customers' willingness to EP about ($\beta = 8\%$) (see Table 5).

6. Conclusion

The effect of the EP system on CS under COVID-19 was proposed successfully based on OLS, fixed effect, and random effect in this study. Moreover, the predicting of CS was also found to be successfully dependent on ANFIS and HyFIS. The questionnaire was collected from 1025 samples who lived in Saudi Arabia during COVID-19. The output variable is determined as CS, but the SE, CT, PV, AT, and CR are input variables. In the results, we found no multicollinearity between variables in the beginning. There were strong positive correlations between output (CS) and input variables except for PV and CT.

Furthermore, there were weak correlations between input variables (CR, AT, PV, CT, and SE). The results also indicate that AVE is above 50%, while CR results are above 70%, and Cronbach's alpha is no less than 70% invalidity and reliability tests consistent with [53, 54]. After that, the OLS, fixed effect, and random effect are used to select significant input variables. In the OLS-indirect effect, the input variables have a significant positive effect on EP with R-square equal to 64%. In addition, the EP has a positive effect where R-square equals 26%. In the OLS-direct effect, the CT, PV, and CR have a significant positive effect on CS, but the SE and AT have no substantial direct effect, the input variables have a significant positive effect on CS, where R-square equals to 56%. In the fixed-indirect effect, the input variables have a significant positive effect on EP where R-square equals 73%.

Furthermore, the EP positively affects CS with R-square equal to 20%. The CT, PV, AT, and CR have substantial positive effects on CS, where R-square equals to 56% in fixeddirect effect. In the random-indirect effect, the input variables have a significant positive impact on EP where R-square equals 71%. In addition, the EP has a significant positive effect on CS, where R-square equals to 26%. In random-direct effect, the CT, PV, and CR have a significant positive effect on CS where R-square equals to 56%. Finally, 10% of CS was predicted after splitting the questionnaires into 90% and 10%. The HyFIS model is better than ANFIS to predict the CS based on lower error criteria ME, MPE, and MAPE.

Data Availability

The data used in this study were collected by the authors using a questionnaire.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The authors extend their appreciation to the Deputyship for Research and Innovation, Ministry of Education in Saudi Arabia, for funding this research work through the project no. 7977.

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