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Economic Growth: The Myth of Economic Sanctions

Siamack Shojai, PhD

Paying for Less Waiting Time on the Golf Course:
A Study Using a Pace-of-Play Simulation Model

Andrew A. Tiger, Colene Trent, Christopher K. Manner

The effect of customer reviews on the perceived user experience of a mobile banking application

Justin Bateh, PhD, Timothy Klaus, PhD

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Siamack Shojai, PhD

William Paterson University

ABSTRACT

This paper uses an Ordinary Least Squares (OLS) method to measure the impact of external shocks such as economic sanctions ("sanctions"), the Iran-Iraq war, and crude oil price shocks on output growth in Iran using data from the 1960-2021 period. Despite the ever-increasing use of sanctions, researchers have no consensus about the definition of the effectiveness of sanctions and the measurement of success (Pala, 2021). The anecdotal evidence presented by various political entities does not provide any empirical (econometrics) analysis of the long-run impact of sanctions on the Iranian economy.

The overall conclusions based on estimation results are that economic sanctions significantly and negatively affect the real GDP and the percentage annual change in the real GDP of Iran seven years after their imposition. Crude oil prices significantly and positively affect real GDP and percentage change in real GDP. The Iran-Iraq war has had a negative significant effect on the real GDP and percentage change in the real GDP of Iran two years after the start of the war. The lagged dependent variable positively affects the percentage change in real per capita GDP and has no impact on real GDP or its percentage change.

Keywords: economic sanctions, growth econometrics, the effectiveness of economic sanctions, per capita GDP.

1. Introduction

This paper uses an Ordinary Least Squares (OLS) method to measure the impact of external shocks such as economic sanctions ("sanctions"), the Iran-Iraq war, and crude oil price shocks on output growth in Iran. The focus on this case stems from the observation that many growth researchers have used panel data (pooled crosssection and time-series) to capture partial derivative of explanatory variables with respect to growth while not being informed by the historical and institutional context of the countries studied (Durlauf et al., 2005; p. 646). This paper provides a brief history of economic sanctions followed by a discussion of the significant issues surrounding the analysis of the effectiveness of economic sanctions. This research uses a growth model to capture the economic impact of sanctions on the target country to overcome the methodology and data difficulties explained in the literature on the effectiveness of sanctions. The empirical results indicate that sanctions significantly impact the economic growth of targets irrespective of achieving the political goal/s set by the imposing countries.

2. Economic Sanctions as the Last Stage of Diplomacy

The modern history of economic sanctions goes back to the first nineteenth century's Pacific blockades imposed in 1827 by Britain, France, and Russia against Turkey in the independence war with Greece (Davis & Engerman, 2003, p. 188). Davis and Engerman present 21 (seven multilateral and 14 unilateral) Pacific blockades from 1827 to World War I against small countries in Europe, Latin America, and Asia as imposed by Britain, France, Italy, and Germany. The League of Nations levied four cases of multilateral sanctions during 1921-1936. With the strong support of the U.S., the United Nations imposed more than 145 sanctions during the 1950s-1990s period.

Despite many studies (Rarick & Han, 2010; Hufbauer & Elliott, 1990; Elliott, 1997; Elliott & Hafbauer, 1999; Pape, 1997,1998; Bergeijk & A.G, 1989; Eaton & Engers, 1999; Hufbauer, 2007; Shojai and Root, 2013,) concluding that in more than two-thirds of cases sanctions have not been effective and no conclusive evidence that sanctions by themselves contribute to the achievement of the goals of sanctioning countries (Smeets, 2018), the global economy has witnessed proliferation of sanctions during the past 23 years. Between 2000 and 2021, the U.S. Treasury's Office of Foreign Assets Control (OFAC) sanction designations against individuals and entities increased by 933 percent, going from 912 cases in 2000 to 9,421 in 2021 (The Treasury 2021 Sanctions Review, the Department of Treasury, p.2). Collins-Chase and Nelson (2023), in an overview of the U.S. sanctions presented to the 118th Congress of the U.S., list major areas of sanctions, including support of international terrorism; nuclear arms proliferation; egregious violation of human rights, democratic governance, or corruption standards, and threatening regional and global stability. The authors suggest that the ultimate goal of the sanctions has been to significantly change the behavior of the sanctioned government or a change in government in the case of Iran and Russia. Some U.S. sanctions are designed to destabilize the target's economy and pressure top decision-makers in the target country. Other sanctions are symbolic in the absence of other hard foreign policy tools.

Despite the ever-increasing use of sanctions, researchers have no consensus about the definition of the effectiveness of sanctions and the measurement of success (Pala, 2021). In a literature review of the effectiveness of economic sanctions, Pala points to studies (Hufbauer et al., 2007) that adopt quantitative approaches to the definition of effectiveness (success of sanctions) and others such as (Pape, 1997) that use qualitative analysis of sanction cases. Pala identifies the chaotic use of the words "effectiveness" and "efficiency" as the central issue in analyzing the impact of sanctions. The author interprets effectiveness as the ability to achieve the stated goals of the sanctions. During all U.S. administrations, from President Carter to President Biden, the sanctions imposed against Iran (Katzman, 2021) have been to change the behavior of Iran in the areas cited above. Therefore, the effectiveness of sanctions imposed on Iran should be assessed by the perceived or realized significant change in Iran's behavior.

3. Sanctions Imposed on Iran

The U.S. imposed the first unilateral sanctions on Iran after the U.S. embassy was taken over in November 1980 following the Iranian revolution of 1979. These relatively modest sanctions banned imports from Iran and froze $12 billion in Iranian assets in the U.S. In 1984, the U.S. State Department designated Iran a State Sponsor of Terrorism and imposed sweeping sanctions against Iran. In 1992, the U.S. Congress passed legislation banning the transfer of goods and technologies related to nuclear and weapons systems in Iran. Later, the Iran –Libya Sanctions Act of 1996, a relatively significant sanction, banned investments of more than $20 million in Iran's oil and gas industries by the U.S. and third-party companies. The act was not implemented until 2010 because of the European Union's objections (Kumar Sen, 2018).

The United Nations Security Council imposed multilateral sanctions on four different occasions during the 2007-2015 period, including Resolutions 1747 (2007), 1803 (2008), 1929 (2010), and 2231 (2015). Except for Resolution 2231, which replaced Resolution 1929, the UN sanctions targeted Iran's nuclear proliferation and missile programs. The European Union agreed to impose targeted sanctions on people, companies, and sectors directly involved in Iran’s nuclear program in 2010 when the U.S. Congress passed the Comprehensive Iran Sanctions, Accountability, and Divestment Act of 2010, which imposed a significant ban on investment in energy sectors and the international banking transaction with Iran.

In summary, the sanction regime on Iran has included periods of unilateral and relatively mild targeted sanctions imposed by the U.S. (The U.S. Congress and Executive Orders) as well as periods of robust, comprehensive, and multilateral sanctions targeting export-imports, access to strategic goods and technology related to nuclear and energy industries, a ban on international transactions with the central bank and banking industry, as well as visa restrictions and freezing of assets of targeted individuals, entities, and foundations. During 2013-2018, the primary sanctions imposed by the U.S. and the EU were waived following a temporary agreement between Iran and the G5+1 (the United States, the United Kingdom, France, Russia, China, and Germany) in 2013. A more comprehensive agreement between the parties mentioned above, known as the Joint Comprehensive Plan of Action (JCPOA), was signed in 2015, which resulted in the UN Security Council Resolution 2231 and the waiver of nuclear-related sanctions by the U.S. and the EU (Kumar Sen, 2018). However, the U.S. withdrew from the JCPOA via an executive order issued on May 8, 2018. During 2018-2023, the U.S. adopted a “maximum pressure” policy to bring Iran to negotiation and possible agreement on a more comprehensive package embracing all disagreements between the parties. The all-inclusive package would possibly embrace Iran’s nuclear activities, regional interferences and disputes, human rights violation issues, cyber and criminal activities, and missile programs. At the time of the writing of this paper, no public announcement has been issued about any possible agreement despite reports of many secret negotiations.

4. Effectiveness of Economic Sanctions

In a qualitative (non-econometrics) Congressional Research Service report prepared for the U.S. Congress, Humud and Thomas (2022) assess the effectiveness of the U.S. sanctions imposed on Iran based on four criteria: effect on Iran’s nuclear program and strategic capabilities, effects on Iran’s regional influence, Iranian domestic political effects, and economic effects. The report indicates that Iran has advanced its nuclear and missile programs despite the international sanction regime of 2011-2015. The sanctions had an insignificant impact on Iran’s regional activities and did not achieve any gradual desired change in domestic politics and human rights issues.

On the economic ground, the authors assert that the sanctions have substantially imposed costs on Iran's economy during 2011-2015, including Iran's Gross Domestic Product (GDP) contracted by 20 percent, its oil exports dropped from 2.5 million barrels per day (mbd) to 1.1 mba by 2014, its foreign reserves abroad declined from $115 billion to $85 billion, its currency depreciated by 757 percent from 2015 to December 2021 (as of June 2023, the depreciation was 1,357 percent), trade between the U.S. and Iran declined from $291 million in 2015 to $40 million in 2020, inflation rate increased to 60% during 2011-2013, and the international banks left Iran (Humud & Thomas, 2022, pp. 50-54).

The anecdotal evidence presented by various political entities does not provide any empirical (econometrics) analysis of the long-run impact of sanctions on the target economy. Scholarly research on the effectiveness of sanctions is ample but suffers from definitional, methodological, and data constraints (Pape, 1997, 1998; Parker, 2000; Oskarsson, 2012; Shojai & Root, 2013). Hufbauer et al. (1990) used an ordinary least squares regression to regress an index of success/failure of sanctions on explanatory variables such as the size of sanction-imposing and target countries, the nature of the relationship of sending and receiving countries before the imposition of sanctions, and the cost of sanctions to the sending entity. The study included 115 cases of sanctions between WWI and 1990. The success/failure index was constructed by the product of experts' opinions on "policy success" (whether sanctions were successful or not) and "sanctions contributions to the policy results," each on a scale of 1-4. The product of these scores produced all possible values of the dependent variable (success/failure index) comprised of 1, 2, 3, 4, 6, 8, 9, 12, and 16. Shojai and Root (2013) scrutinized the methodology adopted by Hufbauer et al. (1990). They concluded that the success/failure of sanctions is a random outcome, and the empirical research results could be flawed because of this randomness.

Other researchers have used a dummy dependent variable, which assumes a value of one for success and zero for failure (Dashti-Gibson et al., 1997). They do not report any short-run statistically significant impact. Dizaji et al. (2013) apply a vector autoregressive model (VAR) to the case of sanctions against Iran's crude oil exports during 2007-2011. They conclude that sanctions have a robust impact on per capita GDP, imports, and gross capital formation, among other macroeconomic variables, during the initial phase of sanctions and lower the probability of success in the long run.

5. Methodology (Growth Econometrics)

Durlauf et al. (2005) distinguish between the neoclassical growth model (Solow, 1956; Swan, 1956) and the endogenous growth theory models of Romer (1986) and Lucus (1988). They argue that there are sophisticated statistical models that can be collectively called growth econometrics (Durlauf et al., 2005, p. 559). They present a generic growth model that regresses the percentage change in per worker/capita growth rate (g) on Solow's original growth determinants (X) as well as the determinants outside Solow's model (Z) as used by many researchers and an error term (e). The model is presented as follows:

$$g_t = a\ log\ g_{t-1} + b\ X + c\ Z + e \qquad (1)$$

Durlauf et al. (2005, p. 608) identify 145 different variables used in Z determinants in the growth literature, with many to be found statistically significant. Unlike the studies cited, this study estimates the impact of Z determinants, namely sanctions, oil price shocks, and war, on the GDP of Iran. Some studies have documented that robust growth determinants include investment as a percentage of GDP, initial income, and population growth (Levine & Renelt, 1992). Kalaitzidakis et al. (2000) found that inflation volatility and exchange rate distortions are robust determinants of growth rates. It can be argued that all these macroeconomic variables are similarly affected by exogenous shocks and will ultimately impact the GDP if the shocks are effective.

This paper uses dummy explanatory variables similar to the model used by Cerra and Saxena (2008) to estimate the impact of exogenous shocks (the dummy variables), including sanctions (Ds), oil price shocks (Do), and war (Dw) on the economic activity in Iran as measured by Iran's GDP and its variants. This model avoids the construction of an expert opinion survey as a measure of sanctions effectiveness, as Hufbauer et al. (1990) did. It simply investigates if sanctions affected Iran's economy as measured by its GDP performance ("sanctions contributions to policy results" in the Hufbauer et al. language). The question of "policy success "as defined by a change in Iran's behavior in the areas included in sanction goals is not the subject of this study. However, as of October 2023, none of the political disagreements between the sanctioning parties and Iran have been resolved. This paper estimates various versions of the model presented below:

$$g_t = a + b \log g_{t-1} + cD_s + dD_O + wD_w + k \, \Delta \, COP + e \tag{2}$$

Where g_t represents the change in the level of real GDP, the percentage change in per capita real GDP at time t, and the percentage change in the level of real GDP in different versions of the model. Using these different measures of economic activity enables us to estimate the dollar amounts and the rate of change in GDP and per capita GDP. The purpose is not just to identify the impact of external shocks but to measure the level and the rate of the impact. As reported in the empirical results, the dummy variables denoted by $D_s,\ D_o,\ and\ D_w$ represent sanction episodes, oil price shock, and war times, respectively. The dummies are equal to one during sanction episodes, crude oil price shock (a decline of crude oil prices by three or more than three percent from the previous year), and war years but zero otherwise. Annual crude oil price (COP), averaged over 12 months of monthly prices, is included outside Solow's model. The error term is denoted by e. The coefficient of dummy variables is expected to be negative, but the coefficient of the lagged dependent variable and COP are expected to be positive. All data are obtained from Federal Reserve Economic Data- St. Louis FED (FRED).

6. Empirical Results

Different Versions of a growth model presented in equations 1 and 2 are estimated using annual data for Iran from 1960 to 2021. The ordinary least squares estimates are presented in Tables 1-4. Time-series data are expected to be not stationary, and the Augmented Dickey-Fuller (ADF) tests indicate that all variables' levels, including COP, have unit roots. However, the first difference of all variables, including COP, is stationary and is used in the regression models. Version A is the bassline OLS regression results and includes all dummy variables, the lagged dependent variable (LDV), and the first difference in crude oil price. Keele and Kelly (2006, pp. 186-205) argue that including the lagged dependent variable in an OLS model could be problematic when residual autocorrelation is detected and causes a downward bias in the estimated coefficient for the explanatory variables. However, they conducted 1,000 Monte Carlo simulations to measure the significance of bias in estimated coefficients and recommend that *"... if history matters, OLS with an LDV remain a good choice, p. 203.*" The economic growth literature (Pritchett, 2000) emphasizes the significance of earlier income levels that would prevent rapid growth in poorer world regions. Levine and Renelt (1992) also identify the role of initial income in long-term economic growth. Therefore, versions A and B of the models retain the LDV; however, version C excludes the LDV to avoid the OLS potential estimation bias. Versions B and C, when warranted, consider the lagged impact of war and sanctions episodes on the dependent variable.

Table 1 presents the OLS results of regressing the first difference of real GDP (stationary) on the explanatory variables listed in the table. Using the first difference of real GDP allows us to estimate the dollar amount of the impact of the explanatory variables. The baseline model (A) indicates that crude oil prices and war significantly impact Iran's GDP. However, the war in its first year positively impacts the GDP, which may result from mobilizing extraordinary resources and efforts to overcome the war. The lagged dependent variable is insignificant in explaining variations in GDP. Version B (Table 1) drops the concurrent dummy variables and measures the impact of sanctions two and seven years after their imposition and the impact of war one and two years after the start of the war. The sanctions impacted GDP negatively and significantly in the seventh year, causing an estimated \$48.6 billion reduction. However, two years after the sanction episode, GDP is positively impacted by an estimated \$67.2 billion. War significantly negatively impacts the GDP in its second year by an estimated \$59.3 billion; however, its first-year effect is positive, as reported before. Higher crude oil prices significantly and positively affect GDP, but the lagged dependent variable is not impactful. Forty-three percent of the variation in GDP is explained by the explanatory variables, as indicated by an R-square of 0.43**.** Version C (Table 1) drops the lagged dependent variable to avoid potential bias in the estimated coefficients, but the estimation results are almost identical to version B. The overall conclusion is that sanctions negatively and significantly affect GDP after seven years of their imposition; war's negative and significant impact is experienced two years into it. However, during the first year of the war, GDP improved. Crude oil price consistency has a significantly direct effect on Iran's GDP.

Table 1: Dependent Variable – The First Difference of Real GDP

Explanatory Variable	Version A Coefficient (t-value)	Version B Coefficient (t-value)	Version C Coefficient (t-value)
Constant	7.17e+9 (0.74)	-8.1e+9 (-0.80)	-8.2e+9 (0.83)
Ds (Sanctions)	-2.09e+10 (-1.39)	-	-
Do (Crude Oil Price)	-5.38e+9 (-0.36)	-	-
Dw (War Years)	4.04e+10 (2.77) ***P	-	-
First-difference Crude Oil Price (COP)	1.27e+9 (2.34) **P	1.8e+9 (3.80) ***P	1.83e+9 (4.00) ***P
Lagged Dependent Variable	0.006 (0.04)	0.03 (0.20)	-
Ds-2	-	6.72e+10 (3.17) ***P	6.73e+10 (3.21) ***P
Ds-7	-	-4.86e+10 (-2.73) ***P	-4.89e+10 (-2.80) ***P
Dw-1	-	4.99e+10 (2.77) ***P	5.04e+10 (2.84) ***P
Dw-2	-	-5.93e+10 (3.80) ***P	-5.86e+10 (-3.21) ***P
R-square	0.28	0.43	0.43
Adjusted R-square	0.21	0.37	0.38
No. Observations	60	55	55

t-values are reported in parentheses. *, **, *** indicate a significance level of 10 percent, 5 percent, and 1 percent, respectively. P indicates a p-value of less than 5 percent. Some coefficients are presented in scientific notation.

Table 2 presents the OLS estimation results for the baseline model (A) and improved versions B and C. The baseline model indicates that the constant and lagged dependent variables are statistically significant at a five percent or higher significance level, but other explanatory variables are insignificant. When insignificant explanatory variables are excluded (version B), constant, DS, and lagged dependent variables become significant at five percent or better with the expected sign. However, the R-square (R^2) is reduced from 0.48 to 0.40. Version C dropped crude oil prices and the lagged dependent variable. However, the estimation results, including the estimated coefficients, resemble version B, except that the model's explanatory power is lowered ($R^2 = 0.08$). Various estimation results (not reported here) indicate that lagged dummies are not significant at any significance level. The conclusion is that sanctions significantly and negatively impact the percentage change in real per capita GDP by an estimated -4.42 percent.

Table 2: Dependent Variable – Percentage Change in Real Per Capita GDP

Explanatory Variable	Version A Coefficient (t-value)	Version B Coefficient (t-value)	Version C Coefficient (t-value)
Constant	7.59 (5.97) ***P	-7.54 (5.77) ***P	4.56 (2.79) ***P
Ds (Sanctions)	--4.32 (-1.78) *	-6.28 (-3.31) ***P	-4.42 (-2.19) **P
Do (C crude Oil Price)	-4.31 (-1.82) *	-	-
Dw (War Years)	1.42 (0.54)	-	-
First-difference Crude Oil Price (COP)	-.0.03 (-017)	0.02 (0.15)	-
Lagged Dependent Variable	1.89 (2.18) **P	1.73 (2.10) **P	-

R-square	0.48	0.40	0.08
Adjusted R-square	0.36	0.33	0.06
No. Observations	29	29	61

t-values are reported in parentheses. *, **, *** indicate a significance level of 10 percent, 5 percent, and 1 percent, respectively. P indicates a p-value of less than 5 percent.

Table 3 presents the OLS estimation results of regressing percentage change in real GDP on the explanatory variables, enabling the estimate of the percentage change in real GDP caused by one unit change in the explanatory variables. The baseline estimation results (A) indicate that the constant and sanctions significantly affect the percentage change in the real GDP of Iran. Version B estimation results indicate that the constant, COP, DS-7, and Dw-2 are significant at five percent or better significance levels and have the expected sign. Sanctions in their second year and war in their first year significantly and positively affect the percentage change in real GDP. This version has the highest R^2 among other versions, equal to 0.39. Version C excludes the LDV and explains 21percent of the variation in real GDP by the constant, Ds-7, and COP, which are all significant with correct signs at five percent or better significance levels. A consistent conclusion is that sanctions demonstrate their negative impact seven years after their inception on the percentage change in the real GDP of Iran by an estimated -16.15 percent.

The impact of economic sanctions on the first difference in real GDP and the percentage change in real GDP are pretty much the same. However, the population growth rate during the 1960-2021 period varied from 0.39 to 5.08 percent annually, declining to below two percent after 1993, when severe economic sanctions came into play. This lowers the measured impact of economic sanctions on the percentage change in real per capita GDP.

Table 3: Dependent Variable – Percentage Change in Real GDP

Explanatory Variable	Version A Coefficient (t-value)	Version B Coefficient (t-value)	Version C Coefficient (t-value)
Constant	15.76 (3.23) ***P	13.25 (2.56) **P	-19.71 (4.40) ***P
Ds (Sanctions)	-14.63 (-2.06) ***P	-	-
Do (Crude Oil Price)	-3.63 (-0.55)	-	-
Dw (War Years)	10.79 (1.68) *	-	-
First-difference Crude Oil Price (COP)	0.34 (1.40)	0.57 (2.65) **P	0.55 (2.51) **P
Lagged Dependent Variable	0.15 (1.20)	0.19 (1.48)	-
Ds-2	-	20.5 (2.11) **P	-
Ds-7	-	-23.75 (-2.86) ***P	-16.15 (-2.88) ***P
Dw-1	-	15.06 (1.83) *	-
Dw-2	-	-27.96 (-3.30) ***P	-

R-square	0.25	0.39	0.21
Adjusted R-square	0.18	0.31	018
No. Observations	60	55	55

t-values are reported in parentheses. *, **, *** indicate a significance level of 10 percent, 5 percent, and 1 percent, respectively. P indicates a p-value of less than 5 percent.

Table 4 presents the OLS estimation results of regressing the logged difference of real GDP and real per-capita GDP on the stationary values of the explanatory time series. The results are comparable to those reported in previous tables. The ADF test indicates that the percentage change in real GDP and real per capita GDP is stationary, and the results in Table 4 support an earlier conclusion.

Table 4: Dependent Variable – Logged-difference Real GDP and Real Per-capita GDP

Explanatory Variable	Dependent Variable: Logged- difference Real GDP	Dependent Variable: Logged-difference Real Per-capita GDP
Constant	0.14 (2.93) ***P	0.04 (2.45) **P
Ds (Sanctions)	-	-0.04 (-2.04) **P
Ds-7 (Sanctions)	--0.13 (-2.29) **P	-
Dw-1 (War Years)	0.26 (3.00) ***P	-
Dw-2 (war Years)	-0.26 (-2.93) ***P	-

Logged-difference Crude Oil Price (COP)	0.23 (2.26) **P	-
R-square	0.33	0.06
Adjusted R-square	0.28	0.05
No. Observations	55	61

t-values are reported in parentheses. *, **, *** indicate a significance level of 10 percent, 5 percent, and 1 percent, respectively. P indicates a p-value of less than 5 percent.

7. Summary and Conclusions

This paper uses the OLS estimation method to estimate the impact of economic sanctions, the Iran-Iraq war, and oil prices (shocks) on Iran's change in real GDP, the percentage change in Iran's real per capita GDP, and the percentage change in real GDP in Iran. Since 1980, the U.S., EU, and the United Nations Security Council have imposed modest and severe sanctions on Iran. Iran was also at war with Iraq from 1980 to 1988. In addition, oil price shocks (reduction of three or more than three percent in annual oil price) have been experienced by the Iranian economy. Data from the 1960-2021 period is used to estimate three versions (A, B, and C) of a basic growth model using dummy explanatory variables similar to the ones used by Cerra and Saxena (2008). Binary explanatory variables equal to one capture the periods of sanctions, war, and oil price shocks. The ADF test indicates that the level of GDP, real per capita GDP, and COP have unit roots and become stationary at the first difference level.

The overall conclusions based on estimation results are: First, economic sanctions significantly and negatively affect the GDP by $48.9 billion and the percentage annual change in the GDP of Iran seven years after their imposition by -16.15 percent. However, sanctions immediately and significantly reduce annual percentage change in real per capita GDP by 4.42 percent. Second, crude oil prices significantly and positively affect real GDP and percentage change in real GDP. Crude oil price shows no impact on percentage change in per capita GDP. Similarly, oil price shocks do not significantly impact the Iranian economy at a five percent or better significance level. Third, the Iran-Iraq war has had a negative significant effect on the real GDP by $ 58.6 billion and the percentage change in the real GDP of Iran two years after the start of the war. The Iran-Iraq war positively impacted the real GDP and the percentage change in real GDP during its first year. This is against the conventional wisdom about the impact of the war. However, immediately after the war, many resources were mobilized to meet the war requirements. Fourth, the lagged dependent variable positively affects the percentage change in real per capita GDP and has no impact on real GDP or its percentage change. Version C of the model drops the lagged dependent variable to avoid any potential bias in estimating the coefficients.

The overall conclusion is that economic sanctions have meaningfully affected the economy of Iran but have not been effective in achieving the sanction goal of changing its government's behavior.

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Paying for Less Waiting Time on the Golf Course: A Study Using a Pace-of-Play Simulation Model

Andrew A. Tiger
Angelo State University

Colene Trent
Union University

Christopher K. Manner
Union University

Abstract

Reducing the interval between parties will lead to an increase in golf course utilization, thus increasing revenue. However, interval reduction also increases waiting time. Research by the Global Golf Advisors shows that golfers are willing to pay a premium for reduced waiting time. This study presents a pace-of-play simulation model that analyzes these competing effects to determine an optimal tee time interval. The results of the model are consistent with anecdotal evidence that an increased tee time interval improves pace of play and has the potential to increase revenue.

Introduction

It is well-documented that golfers are often less than fully satisfied with their experience. A 2018 Golfer Experience Study conducted by the United States Golf Association (USGA) found that overall customer satisfaction with golf courses was at 69 percent, comparable to the satisfaction level of the airlines industry and the post office (Brey & Schoonover, 2018). Not surprisingly, one significant aspect of a round of golf that is a major source of dissatisfaction is waiting. Golf is not alone in this area. If there is something universal about the human condition, it is that we hate waiting. We hate waiting for a table, waiting to check in at a hotel, waiting for flights, or waiting in lines for a ride at a theme park. We hate waiting to hit a golf shot.

The golf industry's strategy to reduce waiting during a round has been to try to change customer behavior through awareness, coercion, or peer pressure, rather than viewing the issue as an opportunity for a business solution. Other industries have changed their experience through a combination of technology, data, and communication to alleviate their customers' frustration and meet their expectations. Restaurants have better data about turnaround times for improved reservation scheduling. Hotels have mobile check-in. Theme parks have apps that provide real-time information about the rides that have the shortest waits. In these cases, customers report enhanced satisfaction because of these improvements (Caruelle, Lervik-Olsen, Gustafsson, 2023). Golf is slowly coming to the same conclusion, and the COVID-19 pandemic has accelerated that process (Yun, 2020).

When the USGA began studying pace of play in 2013, they recognized that tee-time intervals were fundamental to improving pace of play, since longer intervals spread out groups and reduce wait time (Yun, 2020). While this may be apparent, many facility managers have been reluctant to increase intervals for fear of losing inventory and revenue. However, according to Yun (2020), when Maryland's Montgomery County Revenue Authority (MCRA) reopened 9 golf courses in May 2020, they adjusted tee-time intervals from 8 minutes to 12 minutes to limit social interaction. The result was not only an improvement in pace of play, but also higher golfer satisfaction and increased revenue. The average round times on the MCRA courses fell from 5 hours to 4 hours. Due to the improved pace of play, satisfaction soared at 6 of MCRA's courses. At one facility, satisfaction scores jumped by 50 points for July 2020 compared with the same period in 2019. As a result, MCRA's monthly revenue increased 25 percent on a year-over-year basis, despite logging fewer rounds. One of the courses was able to raise fees by 50 percent. MCRA outperformed the expectations set by a USGA study, which showed that golfers are willing to pay green fees up to 9 percent higher for quicker rounds (Yun, 2020).

These results indicate that golf course managers must balance the effects of tee time interval and waiting time to enhance customer satisfaction and maximize revenue. A longer interval can reduce waiting time, and golfers are willing to pay a premium for this benefit; however, increasing the interval between tee times reduces a golf course's capacity, allowing fewer players to be accommodated, resulting in lower revenue.

This study demonstrates that golf course managers can use a pace-of-play simulation model to determine the optimal tee time interval. The model shows that golf courses maximize revenues by considering the financial impact of tee time intervals and waiting time. Golfers are willing to pay premiums for reduced waiting, and a pace-of-play model can help managers determine how waiting times change based on tee time intervals. Any course can use this model to increase revenue.

Background

Revenue management uses applied analytics that predict consumer behavior to optimize product availability and price and maximize revenue growth. The objective of revenue management is not to stimulate product demand, but rather to better convert existing demand into higher revenues. Some applications of revenue management result in increases in profitability without increases in capacity (Bell & Zaric, 2013). Other applications of revenue management enhance revenues while selling the same amount of product.

Charging price premiums and discounting are often associated with revenue management. When managers use pricing as a tool for revenue management, they must develop strategies for offering different prices that are consistent with customer preferences and the demand level. Kimes (2000) has suggested that golf course operators could implement a time-based strategy in which customers are charged a different price based on the level of demand. That is, golf course operators may charge customers a premium (levied a surcharge) during busy times and/or offer a discount during slack or unfavorable times.

Alternatively, golf course operators could use a value-based pricing strategy, whereby customers are charged according to value delivered. A study by the Global Golf Advisors (GGA) demonstrated that golfers are willing to pay more for less waiting time (USGA, 2016). The study was based on surveys with more than 12,000 responses. Specifically, the study found that golfers were willing to pay a 9.1 percent premium for a 15–30-minute reduction in waiting time. Younger golfers (under the age of 40) reported they would be willing to pay a 14.2 percent premium. These findings are similar to consumer behavior in other industries in which limited resources create service disruptions, such as the airline industry, healthcare, and amusement parks. In these industries, resources such as time, capacity, and expertise are limited and not easily increased, and customers are willing to pay for better service. For example, airline customers pay more to select their seats and board earlier (Ban & Kim, 2019). Concierge or retainer medicine allows a patient to pay an annual fee ensuring adequate time and availability of patient care (Castaneda, 2020). Disney World and Disneyland offered a FastPass process in which customers receive pay for a ticket that tells you what time to return to a ride and enter through the FastPass queue. Using FastPass saved customers substantial time over waiting in the Stand By line. Disney removed the FastPass reservation system during the COVID-19 pandemic and replaced it with a personalized itinerary service app called Disney Genie (Disney World, 2021).

Because golfers are willing to pay a premium for reduced wait time, the tools of queuing theory are relevant to a successful revenue management strategy. Queuing theory suggests that inputs and outputs often have nonlinear relationships. In some situations, slight changes in inputs lead to significant changes in outputs. In other cases, changes in the inputs have a negligible effect on output. Understanding these relationships is key to revenue management for golf courses.

Queuing theory states that waiting is a function of the relationship between customer arrival times and service times (Stevenson, 2021). How busy the system is, the system utilization, is defined as

$$Service\ Utilization = \frac{Arrival\ Rate}{Service\ Rate}$$

For example, if the customer arrival rate is 4 per minute, and the system can process 6 per minute, then the system utilization is 4/6 = 67 percent. Most managers want their system, workers, and resources to be fully utilized. However, golf course operators must be aware that increased utilization increases waiting time. The competing desires of golf course operators and customers must be balanced in a revenue management program.

Queuing theory also states that waiting is related directly to variability. That is, greater variability within the system typically leads to more congestion and more waiting. The ideal system is an assembly line where each process in the assembly line takes the same time. No variability exists; consequently, no waiting exists. Unfortunately, the game of golf is highly variable. While this variability can be troublesome for management, it is also one of the joys of the game. A course manager can reduce variability by managing arrivals with tee time intervals. Tee time intervals are appointments that reduce arrival variability; therefore, the remaining variability is due to the act of playing golf.

Although playing time variability can be reduced, it is not the focus of this paper. Rather, the intent of the current study is to promote our understanding of how tee time intervals impact waiting time, revenue, and profitability. Tee times are revenue-generating inventory which are sold to golfers. Courses must decide how many tee times to offer and at what price. The tee time interval controls how many tee times are available; larger intervals reduce the number of tee times since all tee times are limited by daytime hours of operation. According to USGA (2016), most golf courses schedule parties at 7 to11-minute intervals, with some courses setting the interval as high as 13 minutes. The focus of this research is to determine the impact value-based pricing for reduced waiting time will have on the optimal tee time interval.

Methodology

To demonstrate how to establish tee time intervals and pricing to maximize revenue, this paper presents a specific case study based on applying a pace-of-play simulation model for daily play at a golf course. The pace-of-play model used in this study is similar to the model developed by Tiger and Salzer (2004). This model is a discrete-event simulation, which is a commonly used method in operations research for modeling systems with variability and interactions (Hauge & Paige 2001, Law & Kelton 2000, Pritsker

1995, Winston 2001). A similar model was used by Kimes & Schruben (2002) to analyze the impact of tee time intervals on variations in pace of play and revenue per available tee time.

Although originally developed as a classroom simulation teaching aid, this model is "substantial enough to consider pace of play and throughput concerns seriously" (Riccio, 2012, p. 92). There are a number of benefits to using pace-of-play simulation models. First, computer models are safer, quicker, and less expensive. Course managers do not have to evaluate an actual system. Modeling on the actual system is time consuming, expensive, and could create bad experiences for both golfers and course managers/owners. Second, computer models allow outside-of-the-box thinking. Creative, innovative solutions can occur when the experimenter is free to try strategies that may be unconventional or even unrealistic. Occasionally, these strategies produce valuable insights that lead to transformational change. Third, the pace-of-play model can simulate any course based on changing inputs. Finally, this model produces useful metrics, including daily rounds played (completed and in-progress), round length, waiting time, and system utilization.

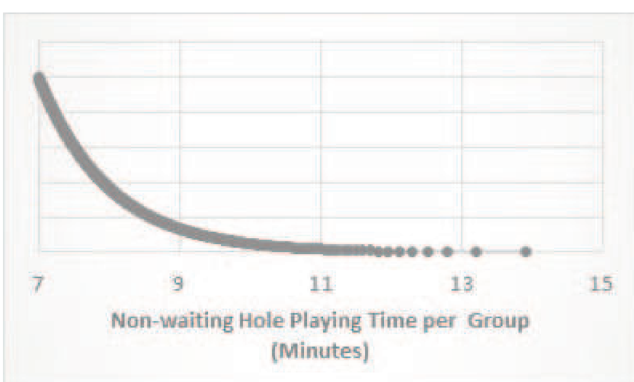
The model was developed using MS-Excel and @RISK, an Excel add-in. This software package has a variety of functions allowing the user to model a gate-management system. The @RISK add-in provides a tool for modeling different scenarios and collecting statistics from multiple replications.

For this case, a fictitious 18-hole par 3 course was modeled. A par 3 course offers a simpler analysis without impeding application to known full length courses. Although the model has the capability of modeling various group sizes, in this analysis, all groups consisted of 4 golfers. For simplicity, each hole is assumed to be identical and the travel time from hole to hole is negligible. The course is assumed to be open 10 hours per day and there are 100 busy days per year. On busy days, there are no no-shows, so all tee times are taken. As a starting point, the current tee time is assumed to be 7 minutes. Only complete rounds are analyzed. The base green fee is $25 and the non-waiting average time to play a hole is 8 minutes.

The time to finish an activity, such as the time to play a golf hole, often follows a distribution with positive skewness, i.e., skewed to the right. For example, in reliability studies, failure times cannot be negative (National Institute of Standards and Technology, n.d.). The physics of the activity provides a lower bound; however, occasionally, odd occurrences can create infrequent, but extremely high times. Consider the situation of changing a flat tire. The time to finish is related to the physical activities: getting tools and spare tire from trunk, using a jack to raise car, removing the tire, etc. There is a minimum time for each of these physics-related activities. However, occasionally, a specific nut cannot be removed, and the time can increase from minutes to hours.

Although this is a fictitious golf course, the model incorporates the principle of positively skewed processing times. Tiger and Salzer's (2004) study of golf time suggests positively skewed distributions for golf activities. The time to play a golf hole is lower bounded by the physical activities of hitting a golf ball and traveling to the next shot. However, occasionally, a player may lose a golf ball, and the time can increase significantly. For this model, processing times follow an exponential distribution. Figure 1 shows the distribution of non-waiting hole times. The most frequent and fastest time is 7 minutes; however, the time to play can be over 11 minutes with the rare occurrence of times close to 15 minutes.

Figure 1 – Distribution of Non-Waiting Hole Times



Using the simulation model, 7 to 13-minute tee time intervals were evaluated. Shorter tee time intervals will load the course more quickly and potentially have the highest rounds played (throughput). Longer tee time intervals place fewer golfers on the course; consequently, less waiting occurs. The benefit of the simulation model is that throughput, round length, waiting time, and system utilization can be plotted for different tee time intervals to show the relationship among these variables.

Figure 2 provides MS-Excel output that shows how a par 3 golf course queuing system was modeled using a spreadsheet. Table 1 provides short descriptions of the spreadsheet logic. The spreadsheet is available upon request. For an 18-hole course with par 4 and par 5 holes, the model is similar but more complex.

Figure 2 – MS-Excel Output for Par 3 Golf Course Queuing System

TWO GOLF HOLE SIMULATION (F9 Key re-simulates)

INPUTS (minutes)	
Tee Time Interval	8.0
Hole #1 Mean Time = 7 +	1.0
Hole #2 Mean Time = 7 +	1.0

PERFORMANCE	1st Hole Idle Time	1st Hole Waiting Time	1st Hole Queue Size	2nd Hole Idle Time	2nd Hole Waiting Time	2nd Hole Queue Size	Time to Finish
Avg	0	9	2	0	5	1	29
Max	0	22	3	5	13	2	40

SIMULATION MODEL (minutes)									KPI						
Group	Arrive to 1st Hole	Begin 1st Hole	Hole Time	Finish 1st Hole	Arrive to 2nd Hole	Begin 2nd Hole	Hole #2 Time	Finish 2nd Hole	1st Hole Idle Time	1st Hole Waiting Time	1st Hole Queue Size	2nd Hole Idle Time	2nd Hole Waiting Time	2nd Hole Queue Size	Time to Finish
1	0	0	9	9	9	9	7	16		0			0		16
2	8	9	8	17	17	17	9	26	0	1	1	1	0	0	18
3	16	17	10	27	27	27	7	34	0	1	1	1	0	0	18
4	24	27	8	35	35	35	8	44	0	3	1	1	0	0	20

Table 1. Description of Spreadsheet Logic

Item	Cell	Description
1	E4	Tee Time Interval. Currently it is set at 8.0 minutes. Every 8.0 minutes, groups are released to the first hole.
2	E5:E6	The average processing time at each hole. The stochastic hole time is generated from an exponential distribution ‘shifted’ to a minimum of 7 minutes by adding 7 to an exponential distribution with a mean, currently set one minute.
3	Column C	Arrive at first Hole. Based on the tee time interval, the time that a group arrives to the first hole
4	Column D	Begin the first hole. If the preceding group is out of the way, the group can begin when arriving. Otherwise, the group will wait.
5	Column E	Hole Time. This is the randomly generated processing time for the first hole. The time is generated from an exponential distribution shifted to a minimum of seven minutes. In Excel, to generate this, the formula in cell E10 is: =7-LN(1-RAND())/E5
6	Column F	Finish first Hole. The time is calendar time the group finishes the first hole.

7	Column G	Arrive at second Hole. Same as the Finish first hole value. No travel time in this model.
8	Columns H – J	Same as columns D, E, and F, except for the second hole.
9	Column L	First Hole Idle Time. If the previous group finishes before the current group arrives, the hole is idle.
10	Column M	First Hole Waiting Time. The difference between beginning and arriving. It is based on if the previous group has not finished prior to the current group arriving.
11	Column N	First Hole Queue Size. Counts the number of groups that have not finished that hole at current time.
12	Columns O – Q	Same as columns L, M, and N, except for the second hole.
13	Column R	Time to Finish. The difference between finishing the second hole and arriving at first hole.

Findings

Figures 3 and 4 show how varying tee time intervals impact rounds played (throughput), round length, waiting time, and utilization. As queuing theory would suggest, changing tee time intervals has a nonlinear impact on each of these variables. Figure 3 outlines the impact of changing tee time intervals on rounds played and round length. Shorter tee time intervals generate the most rounds played; however, there is slight change between 7- and 8-minute tee time intervals. The number of rounds played begins to drop linearly for tee time intervals greater than 9 minutes. Round length experiences significant declines for 7-, 8-, and 9-minute tee time intervals. The reductions in round length are much less significant for 10-, 11-, 12-, and 13-minute tee time intervals.

Figure 3 - Impact of Changing Tee Time Intervals on Rounds Played and Round Length

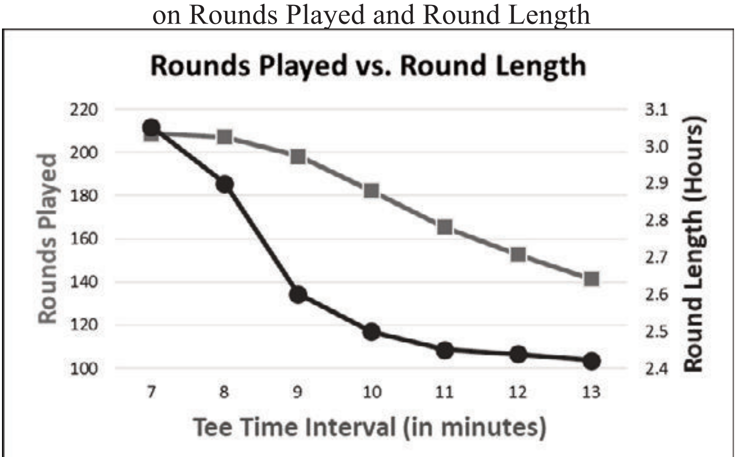


Figure 4 – Impact of Changing Tee Time Intervals on Utilization and Waiting Time

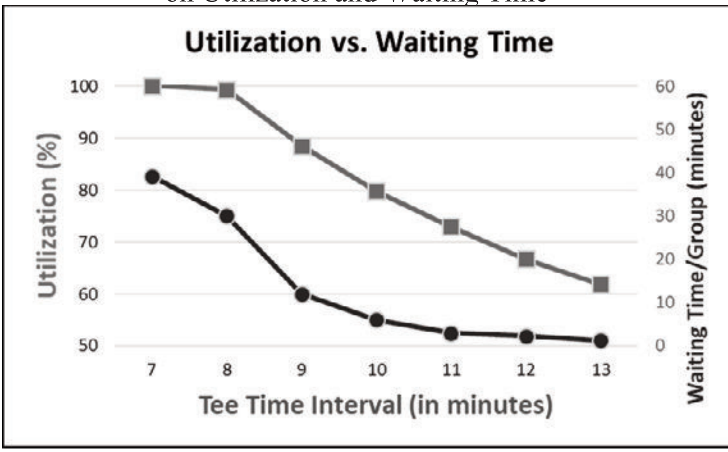
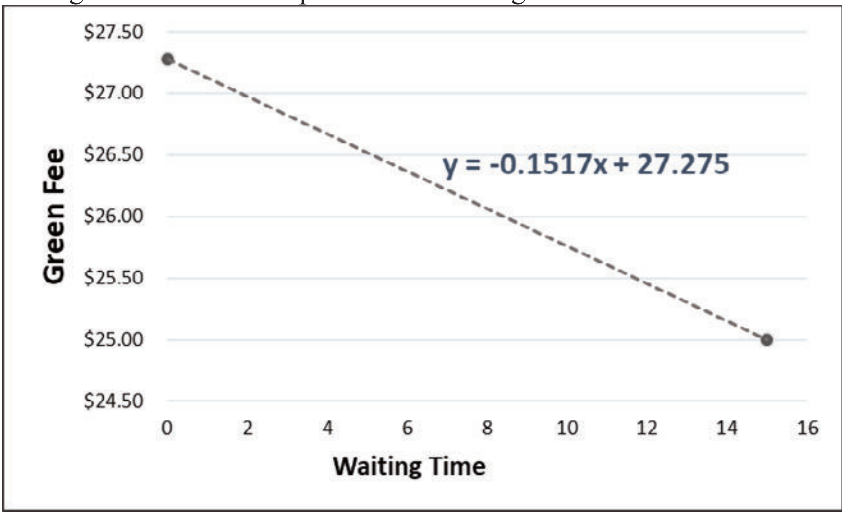


Figure 4 outlines the impact of changing tee time intervals on utilization and waiting time. Course utilization, as measured by the first hole, changes very similarly to rounds played. Shorter tee time intervals generate the highest utilization; however, there is slight change in utilization between 7- and 8-minute tee time intervals. Utilization begins to drop linearly for tee time intervals greater than 9 minutes. Waiting time changes very similarly to round length. Waiting time experiences significant declines for 7-, 8-, and 9-minute tee time intervals. The reductions in waiting time are much less significant for 10-, 11-, 12-, and 13-minute tee time intervals.

Initially, we assume that golfers are paying a $25 green fee at the current 7-minute tee time interval. The average waiting time per group is 39 minutes, and the average number of rounds played per busy day is 209. Therefore, the daily and annual revenue on busy days is $5,220 (209 × $25) and $522,000, respectively, assuming 100 busy days per year.

According to the GGA study, golfers are willing to pay on average a 9.1 percent premium for a 15-minute reduction in waiting time. Using the assumptions of the case, this results in a $2.28 premium. Thus, golfers are willing to pay $27.28 ($25 + $2.28) for the green fee. Assuming a linear relationship, the premium per minute is $0.152, as shown in Figure 5.

Figure 5 –Relationship Between Waiting Time and Green Fee



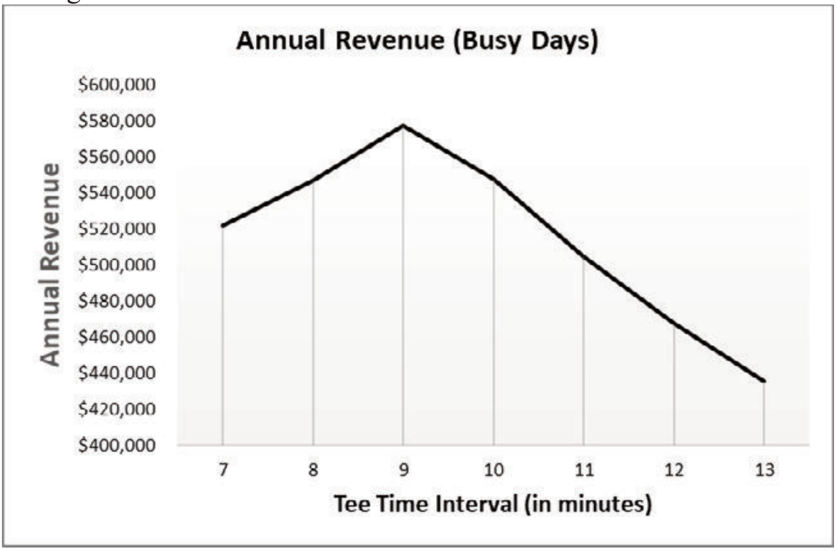
Since waiting time and rounds played are a function of tee time interval, we can calculate green fee, rounds played, daily revenue and annual revenue. These results are presented in Table 2 and Figure 6. Although 9-minute tee time intervals do not maximize rounds played (throughput) nor minimize waiting time, revenue is maximized at this tee time interval. A 9-minute tee time increases revenue by 11 percent relative to the base (7 minute) tee time. Different premiums could produce different results. For example, the GGA study found that younger golfers are willing to pay a larger premium for reduced waiting time, which could move the tee time intervals wider for courses with younger golfers.

Table 2. Revenue vs. Tee Time Intervals

Tee Time Interval (minutes)	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Green Fee	$25.00	$26.38	$29.11	$30.03	$30.48	$30.59	$30.74
Rounds Played	209	207	198	182	166	153	142
*Daily Revenue**	$5,220	$5,467	$5,775	$5,477	$5,048	$4,674	$4,353
*Annual Revenue***	$522,000	$546,665	$577,463	$547,692	$504,770	$467,362	$435,347
% Revenue Change from Base	0%	5%	11%	5%	-3%	-10%	-17%

**Daily Revenue = Rounds Played*Green Fee, ** Annual Revenue = 100 Busy Days*Daily Revenue*

Figure 6 - Annual Revenue as a Function of Tee Time Interval



Conclusion

Reducing tee time interval can increase capacity and revenue. That is, if the amount of time between parties can be reduced, more players can be accommodated, and revenues can be increased. However, a longer tee time interval reduces waiting time and research by the GGA shows that golfers are willing to pay a premium for reduced waiting time. As such, golf course managers must carefully balance these competing effects on revenue.

The current study demonstrates that golf course managers can determine an optimal tee time interval using a pace-of-play simulation model. The results of this study showed the impact of a 9.1 percent premium for a 15-minute reduction in wait time. However, different premiums could produce different results. For example, the GGA study found that younger golfers are willing to pay a 14.2 percent premium for reduced waiting time, which could move the optimal tee time interval even longer.

This case illustrates that golf course revenue can be maximized based on the GGA financial impact research and an analysis of the impact of tee time intervals and waiting. Golfers are willing to pay premiums for reduced waiting, and pace-of-play models give course managers the ability to determine how waiting changes based on tee time intervals. Additionally, the pace-of-play model is designed to model any course, offering the golfing community a powerful tool for increasing revenue.

Although the results of this study have important implications for golf course management, the model limitations should be recognized. First, this study used a fictitious golf course as the basis for analysis. This simplification clearly diminishes model reality. However, the purpose of this study was to demonstrate that improvements in the revenue-generating ability of a golf course exist by combining longer tee time intervals with an appropriate premium for reduced waiting time. This can be done without modeling an actual 18-hole golf course. Second, several factors that impact pace of play are not modeled, such as each golfer's stroke and subsequent movement to the golf ball's location. This also lessens the model reality. Third, an increase in green fees and fewer golfers would lead to a drop in food, beverage, and pro shop sales. The current study does not account for this loss of revenue. Finally, implementing the results of this study could be challenging. The game of golf is steeped in tradition and slow to change. However, the revenue-generating opportunities demonstrated in this study should not be ignored.

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The effect of customer reviews on the perceived user experience of a mobile banking application

Justin Bateh, PhD
Florida State College at Jacksonville

Timothy Klaus, PhD
Texas A&M University-Corpus Christi

Abstract

In an era overwhelmed by mobile applications, there is a compelling interest among marketers and software developers to comprehend the key factors determining an app's success. Online reviews' significance in shaping user perceptions is explored in the context of mobile applications. We adopted a scholarly approach to examine the effects of online reviews on perceived user interactions. The study comprised a survey for gathering data, accompanied by an online review intervention for a specific mobile banking application. The results suggest the perceived attributes of reviews, such as credibility and usefulness, are vital for influencing perceived user experience. Interestingly, the study indicates that customer reviews do not have a substantial impact on the perceived user experience in terms of its perceived simplicity and usefulness. Nevertheless, a noticeable change emerged in the perceived structured assurance of the mobile banking application between the periods before and after the online review intervention. The conclusions drawn from this study offer original contributions to the research domain of online consumer reviews, illuminating novel insights into how online consumer reviews could affect the perceived user experience.

Keywords: *Reviews, User Experience, Perceived Ease of Use, Perceived Usefulness, Structured Assurance, Reviews Characteristics, Review Credibility, Review Helpfulness, Mobile Banking Application*

Introduction

Mobile applications, commonly known as mobile apps, have been an integral part of modern life for the past decade (Tafesse, 2021). Globally, the unprecedented use of smartphones has made mobile apps a standard way for users to accomplish various essential activities in their daily routines (Dhar & Bose, 2022). Consumers apps extend beyond socializing and making online shopping easy. For instance, there are contemporary mobile apps to help users to track their health, keep their weight aligned with goals, design their travel itinerary, keep a record of income and expenses, and complete banking transactions without visiting a bank. Previous studies have focused on travel, health, and other mainstream mobile applications to understand their user experience (Bakar et al., 2020; Fang et al., 2017; Kenny et al., 2016; Yan et al., 2021). However, there is a need for more literature on mobile banking apps, which are among the most common applications in the current era (Yuen, 2022). The current study focused on mobile banking applications to examine how customer reviews influence the perceptions of consumers who are considering the app.

There were around 1.6 million active mobile apps available in 2022 (Turner, 2023). and 8.1 billion mobile apps were downloaded that year. The growing user demand for mobile banking apps has led to banks restrategizing their marketing campaigns to ensure visibility for a more significant number of downloads on third-party forums, such as App Store or Play Store. Tafesse (2021) pointed out that only 70 percent of Play Store apps reached the threshold of 1,000 downloads. Consequently, in the face of competition, there is an urgency among the developers of mobile banking applications to determine whether online customer reviews significantly impact perceived user experience. Particularly, as bank customers who use the mobile banking app may not go to the bank, the mobile banking app can create a significant labor cost reduction for the bank.

Several researchers have identified success factors for mobile app developers, including the app’s usefulness, subscription fee, software version, size, and number of features (Harris et al., 2016; Ho & Chung, 2020; Hsu & Lin, 2015). In the competitive industry of mobile banking applications, user experiences and subsequent reviews and ratings play a pivotal role in determining the apps’ market penetration and influence on user perception. Online consumer reviews (OCRs) include user-generated content about the degree to which users like the application, which could influence potential users’ behavior to download and use the app. OCRs are a form of electronic word of mouth (e-WOM). which has been influential at several stages during consumers’ decision-making process (Yaylı & Bayram, 2012). Users consider OCRs credible sources, providing information about customers' experience of mobile applications. Dhar and Bose (2022) found that customers' reviews of and preferences for online product design significantly influence the extent of digital goods and services adoption. Researchers have studied the same phenomenon though studies on the emotions and sentiments behind OCRs and their links to customer perception (Dhar & Bose, 2022). factors influencing online reviews and ratings (Tafesse, 2021). and sales of mobile applications (Liang et al., 2015).

The purpose of the current study was to examine the extent to which OCRs impact perceived user experience. *Perceived user experience* is a collective term to represent perceived ease of use, perceived usefulness, and structured assurance. Previous research suggests these factors could help measure perceived user experience (Papakostas et al., 2021). With this study, we sought to help marketers, software developers, and related organizations understand and reaffirm whether customer reviews are relevant to perceived user experience. Additionally, given the emphasis on the type of reviews users encounter, we also focused on the impact of perceived review credibility and helpfulness on the perceived user experience.

The study focused on perceived ease of use, usefulness, and structured assurance following the technology adoption model (TAM). which suggests these factors are the primary determinants impacting the intention to use new technology (Keni, 2020). Because banking mobile applications are digital software designed to make financial transactions easy for humans, it is necessary to understand whether OCR impacts the perceived ease of use, usefulness, and structured assurance of mobile banking app users.

This study brings several contributions to the literature. First, this paper expands on previous research with an examination of perceived review credibility and helpfulness on perceived user experience, finding they significantly impact perceived user experience. Second, this study contributes to the research field of OCRs by identifying ways that reviews impact users' experience with the app. Third, this study finds that reviews significantly impact the structured assurance of a user, an unexamined topic in prior studies.

The following sections present the literature review, methodology, data collection and analysis,and demographic analysis. We discuss the e-WOM's impact on user-perceived experience, the target subject under study. The results and discussion section includes the results of statistical analysis to support or reject the hypotheses. Finally, we conclude the study and provide implications for research and practice.

Literature review

The rapid growth of mobile application downloads has increased the perceived risk of user privacy and security. Harris et al. (2016) identified seven million malware variants in mobile applications, posing a risk to consumers' data. Privacy concerns become more prominent for mobile banking applications, as a user's hacked account could lead to a direct financial loss. Knowing if the application is safe and within a secure banking environment is important for users to minimize risk of information breach or financial loss (Abu-Taieh et al., 2022; Harris et al., 2016). Beyond privacy concerns, many users also regard price as a factor. Even though most mobile banking applications are free for users, banks may charge fees for some services (Huang & Korfiatis, 2015). This section presents a critical review of factors addressed in the existing literature focuses to present the study's conceptual model.

Theoretical framework

According to the literature, TAM, coined by Davis in 1989 (Silva, 2015). and the unified theory of acceptance and use of technology model (UTAUT) by Venkatesh et al. (2003). users' perceptions about the technology impact their attitudes and behaviors. An individual's acceptance of a new version of information technology (e.g., mobile banking applications) depends on their perceptions of usefulness, ease of use, and other common factors. UTAUT, an extended theoretical framework of TAM, came about when authors identified factors like social influence, perceived trust, and facilitating conditions of using the technology, which play a substantial role in building positive user intention (Widanengsih, 2021).

In the context of mobile banking applications, perceived ease of use is the degree to which people think it would be easy to use the application's features, check their account balance, and conduct financial transactions (Keni, 2020). Similarly, perceived usefulness reflects the extent to which consumers think using the mobile banking application would benefit their performance or make their everyday tasks more efficient and less costly (Widanengsih, 2021). Other attributes of the UTAUT model, such as perceived trust and facilitating condition, reflect users' confidence in mobile banking applications and organizations (i.e., banks) that the bank will handle their transaction safely while keeping their personal information safe (Le et al., 2020). Researchers have statistically tested the impact of these variables on user intention to download and use mobile banking applications (Abu-Taieh et al., 2022; Le et al., 2020; Widanengsih, 2021). Abu-Taieh et al. (2022) found that perceived risk, perceived trust, social influence, and service quality significantly impacted the behavioral intention of people in Jordan to use mobile banking applications. However, the study concluded that facilitating conditions, such as assurance about the mobile banking structure, were insignificant in this model. In a similar context, Widanengsh (2021) also used TAM theory to measure the degree to which consumers' interest in mobile banking apps' use varies. The author surveyed 100 banking customers of state-owned banking institutions in Jakarta and concluded that perceived usefulness does not significantly impact consumer attitudes or their interest in a mobile banking application. Whereas perceived ease of use significantly influences consumer attitudes toward mobile banking applications, it fails to affect consumer interest in the same apps (Widanengsh, 2021). Consequently, the past literature on mobile banking applications has yielded mixed results, indicating the need for the current analysis.

Online reviews' impact on user-perceived experience

Researchers have argued that sales of or inclination toward downloading an application depend on the credibility of online ratings and reviews. Lo and Yao (2019) found that reviews written by experts in the hospitality industry were perceived to be more credible and helpful in making a purchase decision for travelers than reviews from people who had yet to experience the same services. Other researchers found that online reviews and ratings (positive or negative) and the language used within have varying impacts on consumer purchase decisions (Benelli, 2020; Changchit et al., 2021, 2022; Kim et al., 2017). In the context of mobile banking applications, marketing researchers have emphasized the factor of social influence (i.e., e-WOM or online ratings and reviews) and found a significant influence on user intention and attitudes (Arruda Filho et al., 2022; Elhajjar & Ouaida, 2020; Shankar et al., 2020; Singh & Srivastava, 2020).

Elhajjar and Ouaida (2020) used social influence in terms of subjective norms, defining it as the extent to which a user perceives their peers, friends, and family believe the mobile banking app is useful. The researchers studied the behaviors of 320 Lebanese mobile banking application users and concluded that social influence significantly influenced their decision to download the application and their expectations of user experience. Researchers have also found social influence to affect users' knowledge about a product (Liang et al., 2015) and help users identify or shortlist products that match their needs (Chen & Xie, 2008).

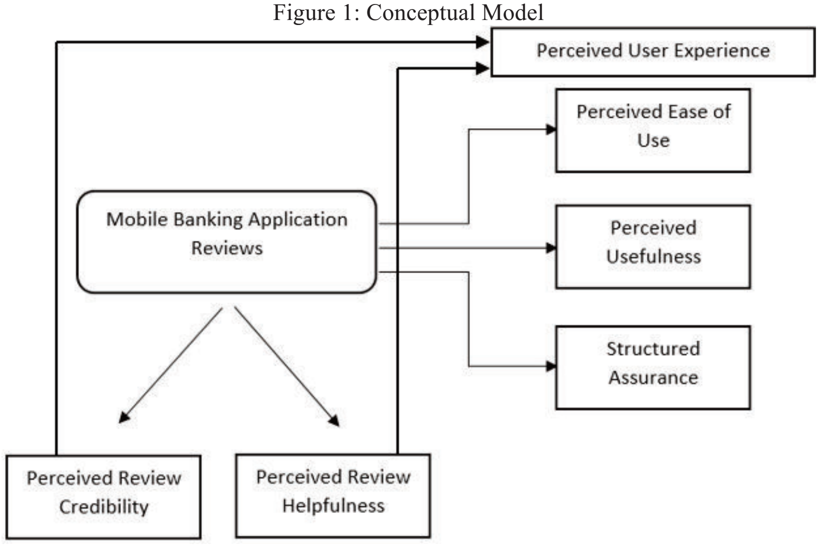
In an examination of e-WOM and its effect on adoption, Shankar et al. (2020) defined e-WOM as positive or negative reviews by existing customers about any service, product, or a brand. Studies on e-WOM are not necessarily limited to social networking sites, blog posts, and news groups, but also include reviews and ratings from Google's Play Store and Apple's App Store. As a digital extension of traditional word of mouth, e-WOM has several unique characteristics, such as the round-the-clock availability of online reviews, the option for exchanging information, the wider reach of reviews posted online, and more credibility. The factor of credibility as one of the characteristics of online review is significant to ensure the information is influential and useful enough for the receiver (Daowd et al., 2021). Kim et al. (2017) examined how potential consumers perceived the product reviews found on third-party platforms and websites where the reviewers remain anonymous and share their post-use experiences. The study found that many consumers think people sharing information related to a product or service experience are likely to have prior experience with or an expert level of understanding the subject matter. The authors noted that when people receive feedback or other information from existing customers, they perceive the reviews as generated by expert product reviewers and readily trust and incorporate the reviews into their decision-making (Kim et al., 2017). This finding suggests that online reviews help potential users see what others think about a particular good or service. Accordingly, Muda and Hamzah (2021) argued that consumers perceive online reviews posted by customers as more credible and valuable because existing customers are not perceived to have any commercial interest or bias.

Dhar and Bose (2022) investigated the characteristics of online reviews, studying the sentiments, emotions, and reactions behind them and how they affect customer ratings. In a qualitative study, the researchers argued that many existing OCRs are confusing and frustrating, with the potential to turn away prospective users from downloading the application. Online reviews are often rich in content and may include text, emojis, and star ratings. Many researchers, such as Liang et al. (2015). have explored which customer reviews encourage users to download or buy a subscription to the mobile application. The authors used multi-facet sentiment analysis to measure customer reviews with a positive or negative impact and argued that reviews can be measured in volume and valence. A high volume of online reviews on a specific application could mean the mobile app's use is widespread, whereas valence reflects the sentiment of the existing consumer to be negative or positive (Liang et al., 2015). Consequently, the sentiment of the review is mainly reflected in user-provided numerical terms. Hence, a positive review perceived as credible and valuable could encourage a purchase. In contrast, a negative review is likely to sway customers away from the product or service experience. The unstructured nature of online reviews found on the App Store or Play Store calls for advanced analysis to measure their impact on users' perceptions of mobile banking applications.

Few studies have investigated the direct impact of online reviews on the perceived structured assurance of mobile banking applications. Structured assurance is the degree to which consumers believe guarantees, regulations, or other procedures exist to promote success (Sha, 2009). In regard to mobile banking apps, we define *structured assurance* as the degree to which customers believe that appropriate security and other measures are in place to conduct banking transactions safely. Some researchers have emphasized the impact of online reviews on perceived trust and risk of using new technology or shoppers' purchase decisions (Kaur & Arora, 2020; Ventre & Kolbe, 2020). These studies reaffirm research showing a mobile banking app's download rate depends on the extent of users' trust in its structure to ensure their personal information and transactions are secure. Kang et al. (2022) found that potential users try to reduce perceived function risks of new products and technology by relying on users' experiences and opinions of before making a decision. Erkan and Evans (2016) defined online reviews as rich user-generated content that helps to reduce information asymmetry by confirming prior consumers' positive or negative experiences. However, whether online reviews impact perceived structured assurance for users of mobile banking apps remains unanswered.

Based on the identified research gaps and factors measuring user-perceived experience, we examined the impact of mobile banking app reviews on perceived ease of use, perceived usefulness, and structured assurance. In addition, we investigated whether perceived credibility and helpfulness of reviews impact perceived user experience. We proposed the following conceptual model:

Figure 1: Conceptual Model



Note. The model reflects the impact of mobile banking application reviews on perceived user experience.

Based on the given constructs/measures of perceived user experience, we tested the following hypotheses:

H1: The mobile banking application's online customer reviews have a positive relationship with perceived ease of use of the mobile banking app.

H2: The mobile banking application's online customer reviews have a positive relationship with perceived usefulness of the mobile banking app.

H3: The mobile banking application's online customer reviews have a positive relationship with structured assurance of the mobile banking app.

H4: There is a significant impact of perceived review credibility on perceived user experience.

H5: There is a significant impact of perceived review helpfulness on perceived user experience.

Methodology

The survey comprised adaptations of scales developed in prior studies. The questions used to measure structured assurance were adapted from Zhou (2012). questions for perceived helpfulness were adapted from Sen and Lerman (2007). questions for perceived credibility were adapted from Chih et al. (2013). and questions used to measure perceived ease of use and perceived usefulness were adapted from Venkatesh and Davis (2000) and Venkatesh et al. (2003).

The first section of the questionnaire presented questions regarding participants" demographic characteristics: age, gender, marital status, ethnicity, education, employment status, and previous experience of using a mobile banking app. The second section included 6-point Likert scale prereview (pre-intervention) questions related to perceived ease of use, perceived usefulness, and structured assurance. In the third section, participants read three positive reviews and ratings. The fourth section comprised 6-point Likert scale postreview questions related to perceived ease of use, perceived usefulness, and structured assurance. We statistically compared the constructs of perceived user experience, measured before and after reading the positive reviews. We expected the positive reviews would have a significant and positive effect on perceived user experience. The study had a pretest–posttest design, a quasi-experimental approach that involved an intervention of reviews and ratings to test perceived user experience. The quasi-experimental design enabled participants to complete the survey before and after the intervention.

Data collection

The participants were 204 customers who visited the bank for different reasons, such as depositing/withdrawing funds, opening a new account, problem resolution, finding a loan, and other purposes. Data collection occurred after receiving their voluntary consent to participate in the research. The consent form included all the information related to the study to ensure ethical considerations. All participants received a $20 gift card to a local grocery store upon survey completion and mobile banking app use.To ensure the participants' privacy, the survey did not include any personal questions that could disclose their identity. Data were stored on a password-protected device.

Data analysis

The data collected from 204 respondents underwent analysis using IBM SPSS 25. We removed extreme outliers with the help of SPSS's box plots, which left a final sample size of 172. Moreover, one of the 63 items (variables) did not assume normal distribution based on acceptable skewness (+/-3) and Kurtosis (+/-8) values and was excluded from the analysis.

We applied data quality checks, which included Cronbach's alpha and principal component analysis (PCA). Cronbach's alpha is a valuable tool to measure the internal consistency reliability of survey items (Taber, 2018). Taber (2018) recommended a threshold of 0.7 to accept internal consistency. All constructs had an alpha score more significant than the assumed threshold of 0.7 (see Table 1).

Table 1: Reliability test

Constructs	Alpha score	*N* items
Social influence	0.798	3
Prereview perceived ease of use	0.876	3
Prereview perceived usefulness	0.857	3
Structured assurance	0.824	3
Perceived review helpfulness	0.926	9
Review credibility	0.939	12
Postreview ease of use	0.916	3

Factor analysis using PCA helped to determine construct validity (see Shrestha, 2021). Computing PCA using SPSS occurred based on the constructs of the conceptual framework. Bartlett's and KMO tests for each factor indicated statistically significant results, indicating the ability to perform factor analysis. Accordingly, the individual PCA results for all constructs showed that the items load into their respective constructs.

Demographic analysis

Table 2: Demographics

		Frequency	Percent	Valid percent
Gender	Male	49	24.0	24.1
	Female	154	75.5	75.9
	No response	1	0.5	
Total		204	100.0	
Highest education	High school	141	69.1	69.1
	Associate’s degree	42	20.6	20.6
	Bachelor’s degree	16	7.8	7.8
	Master’s degree	4	2.0	2.0
	Doctoral degree	1	0.5	0.5
	Total	204	100.0	100.0
Age	18-25	51	25.0	25.0
	26-35	57	27.9	27.9
	36-45	39	19.1	19.1
	46-55	26	12.7	12.7
	56-65	22	10.8	10.8
	Above 65	9	4.4	4.4
	Total	204	100.0	100.0
Ethnicity	African American	11	5.4	5.4
	Anglo	36	17.6	17.7
	Asian	6	2.9	3.0
	Hispanic	143	70.1	70.4
	Native American	7	3.4	3.4
	No response	1	0.5	
	Total	204	100.0	
Marital status	Single	93	45.6	45.8
	Married	85	41.7	41.9
	Divorced	20	9.8	9.9
	Widowed	5	2.5	2.5
	No response	1	0.5	
	System	204	100.0	
Employment status	Full-time	137	67.2	67.5
	Part-time	26	12.7	12.8
	Retired	18	8.8	8.9
	Not employed	22	10.8	10.8
	No response	1	0.5	
	Total	205	100.0	

		Frequency	Percent	Valid percent
Current enrollment	Not a student	162	79.4	80.6
	Full-time undergraduate	20	9.8	10.0
	Part-time undergraduate	16	7.8	8.0
	Full-time graduate	1	0.5	0.5
	Part-time graduate	2	1.0	1.0
	Total	3	1.5	
	System	201	100.0	

According to the frequency and percentage analysis, the sample was significantly female (75.9 percent) compared to male (24.1 percent). Most participants had completed high school (69.1 percent). followed by an associate's degree (20.6 percent). The age of most respondents in the sample was 26–35 years (27.9 percent); only 4.4 percent were over 65 years. Concerning ethnicity and marital status, 70.4 percent of participants were Hispanic, and 45.8 percent were single. The majority of respondents worked full time (67.2 percent) and were not students (80.6 percent). The reviews of this app served as an intervention.

We conducted a paired sample t test and multivariate regression (general linear model) in SPSS 25 to test the hypotheses and determine the links between reviews (and their characteristics) and perceived user experience.

Results and discussion

Paired-sample t tests were conducted to determine if perceived user experience of the mobile banking app had a significant difference before and after the respondents read three positive reviews about the app. The results showed no significant difference between the average score of prereviewed perceived ease of use (M = 5.52) and postreviewed perceived ease of use (M = 5.47, t = 0.964, p = 0.337). A similar result emerged in the case of perceived usefulness, with no significant difference between the prereviewed perceived usefulness score (M = 5.63) and postreviewed perceived usefulness (M = 5.58). t = 1.03, p = 0.304. Thus, the data analysis did not support H1 and H2, indicating that customer reviews do not have a positive relationship with perceived ease of use and perceived usefulness. In the case of structured assurance (H3). the study sound a significant difference, t = -2.206, $p < 0.05$. The postreview structured assurance average score (M = 5.32) is significantly greater than the prereview score (M = 5.21).

and thus H3 is supported by the data analysis, indicating that customer reviews have a very positive relationship with structured assurance of a mobile banking app.

Table 3: Paired Sample Statistics

		Mean	*N*	*SD*
Pair 1	Prereviewed perceived ease of use	5.5203	172	0.67432
	Postreview perceived ease of use	5.4757	172	0.68205
Pair 2	Prereviewed perceived usefulness	5.6263	172	0.61544
	Postreview perceived usefulness	5.5849	172	0.60620
Pair 3	Structured assurance	5.2182	172	0.81965
	Postreview structured assurance	5.3248	172	0.74466

Table 4: Paired Samples Test

		Paired differences		*t*	*df*	Sig.
		Mean	*SD*			
H1	Prereviewed perceived ease use - postreview perceived ease of use	0.044	0.606	0.964	171	0.337
H2	Prereviewed perceived usefulness - postreview perceived usefulness	0.041	0.526	1.031	171	0.304
H3	Structured assurance - postreview structured assurance	-0.106	0.633	-2.206	171	0.029

The data analysis suggested that the structured assurance regarding the mobile banking application was enhanced after reading the three positive reviews. In other words, customer reviews have a significant impact on the perceived user experience in the context of structured assurance or perceived safety. Previous research suggests that online customer reviews have a significant positive effect on structured assurance or perceived safety. Studies have shown that helpful product or service reviews highly influence customers' perceptions and decision-making (Majumder et al., 2022). Moreover, online reviews positively affect initial online trust and customer satisfaction (Torabi & Bélanger, 2021; Wu et al., 2010). Research further suggests that online customer reviews influence structured assurance by reducing consumer risk perceptions triggered by negative emotional polarity (Kang et al., 2022). Online customer reviews' perceived derived attributes directly impact overall attitude toward adopting e-WOM that could develop online trust (Elwalda et al., 2016). Moreover, online reviews positively influence consumer confidence and product safety (Watson & Wu, 2022). The evidence from these studies and ours supports the positive impact of online reviews on structured assurance.

To analyze H4 and H5, we examined the effects of perceived review helpfulness and review credibility on perceived user experience. A multivariate analysis (general linear modeling) was conducted, and a bivariate Pearson correlation between the two constructs showed significant and positive relationships between perceived review helpfulness and postreview perceived user experience as well as review credibility and postreview perceived user experience. Thus, H4 and H5 were supported.

Table 5: Correlations

		Postreview perceived ease of use	Postreview perceived usefulness	Postreview structured assurance
Perceived review helpfulness (H4)	Pearson correlation	.549**	.417**	.427**
	Sig. (2-tailed)	0.000	0.000	0.000
	N	172	172	172
Review credibility (H5)	Pearson correlation	.567**	.568**	.555**
	Sig. (2-tailed)	0.000	0.000	0.000
	N	172	172	172

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

As Table 5 indicates, data analysis suggested an overall significant impact of the review characteristics on the three outcomes (perceived usefulness, perceived ease of use, and structured assurance) as observed by Pillai's trace and other statistics. Thus, review credibility significantly and positively influences the three constructs of perceived user experience when perceived review helpfulness is controlled.

On the other hand, the effect of perceived review usefulness was insignificant on postreview perceived usefulness and postreview structured assurance at the 0.05 level when review credibility is controlled. This outcome shows that although moderate to strong correlations exist between the perceived review helpfulness and perceived user experience variables, the regression model shows an insignificant relationship. There may be different explanations for the loss of significance; for instance, the control variable (review credibility) could be a confounding variable previously omitted from the model or a mediator that fully mediates the relationship between perceived review helpfulness and perceived user experience.

Table 6: Parameter Estimates

Dependent variable		*B*	Std. error	*t*	Sig.	95% confidence interval	
						Lower bound	Upper bound
Postreview perceived ease of use	Intercept	1.993	0.343	5.816	0.000	1.316	2.669
	Perceived review helpfulness	0.307	0.075	4.102	0.000	0.159	0.455
	Review credibility	0.358	0.076	4.718	0.000	0.208	0.508
Postreview perceived usefulness	Intercept	2.843	0.318	8.947	0.000	2.216	3.470
	Perceived review helpfulness	0.085	0.069	1.227	0.222	-0.052	0.222
	Review credibility	0.438	0.070	6.230	0.000	0.299	0.577
Postreview structured assurance	Intercept	1.966	0.393	5.001	0.000	1.190	2.742
	Perceived review helpfulness	0.136	0.086	1.578	0.116	-0.034	0.305
	Review credibility	0.506	0.087	5.809	0.000	0.334	0.677

Previous researchers (e.g., Kim et al., 2017) also claimed that review characteristics such as credibility and helpfulness significantly influence user experience. Review credibility and relevance significantly affect the impact of online product reviews (Mumuni et al., 2020). Helpful reviews could significantly influence purchase intention (Pongpatipat, 2014).

Conclusion and Implications

This study makes several contributions. The results suggest that online reviews are only sometimes helpful in influencing the perceived ease of use and usefulness of mobile banking applications. The result of paired samples t test contrasts with researchers such as Elhajjar and Ouaida (2020) and Liang et al. (2015). who confirmed that reviews from existing users or social influence significantly impact overall expectation of ease of use and usefulness of a mobile banking application. However, Chen and Xie (2008) found that most people view online reviews as information sources to identify and shortlist products that match their expectations. This study's results support the positive significant influence of structured assurance on perceived user experience in banking application use. These findings align with Erkan and Evans (2016) and Kang et al. (2022). who found that online reviews from existing customers help users understand the risk involved in using new technologies. Reviews are crucial to determine how safe and secure specific applications are with users' personal information; hence, they can significantly impact users' level of perceived assurance from the structure of banking applications.

This study also contributes to the research on OCRs by finding that characteristics of reviews, such as perceived level of credibility and helpfulness, significantly impact the perceived user experience of mobile banking applications. Online reviews play a significant role in forming the perceptions and expectations of potential users. Most of the feedback or information in the reviews comes from existing customers or industry experts (Daowd et al., 2021; Kim et al., 2017).

Regarding management implications, banking companies with online banking apps need to collect and post reviews of their mobile banking applications. This action may include enabling and facilitating existing customers to provide feedback on the app's performance. More reviews on app publishing platforms could be crucial for an app's success, enhancing its visibility and attracting more users. System designers could gain valuable information from negative feedback to improve the app, creating a more user-friendly interface and features desired by customers. Designing improvements could include prompting or incentivizing users to leave a review, engaging with users, and simplifying the review process.

Limitations are inherent in many empirical studies collecting data from participants. This study's data collection was limited to a sample of bank customers who came into five bank branch locations in one Southern U.S. city. It would be of interest in future studies to investigate bank customers across a larger region. The respondent' demographics of 75.9 percent female, 70.1 percent Hispanic, and 10.3 percent with a bachelor's or a graduate degree is not representative of the country overall. A more diverse sample could present other perspectives.

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