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ABOUT WIJAR

Westcliff International Journal of Applied Research (WIJAR) is a multidisciplinary, double-blind peer-reviewed, open access journal pioneered by the faculty at Westcliff University. The journal was founded in 2017 and provides an opportunity for academics, industry professionals, and students to publish innovative research that offers insight into practical implementation. In order to widely disseminate new knowledge and scholarship, WIJAR advocates for all submissions to be written in a style that is accessible/available to a broad audience or readership, including those readers who may not be familiar with either research or the topic studied. The journal aligns with Westcliff University's mission to educate, inspire, and empower individuals through its dedication to supporting authors in the review and revision process to produce the highest quality content possible.

Distinguishing this journal from others similar is the strong support offered to contributors, especially first-time authors who may need additional writing or structural assistance. All contributors have access to the Westcliff University Online Writing Center where dedicated research/writing specialists are able to offer support and suggestions.

LETTER FROM THE EDITOR-IN-CHIEF

December 2023.

Dear Readers,

On behalf of the *Westcliff International Journal of Applied Research* (WIJAR) Editorial Board, I am pleased to introduce this issue to our readers. We take great pride in presenting the innovative studies and insightful viewpoints that our authors have uncovered. May their contributions serve as a catalyst for more investigation and motivate others to express their own distinct opinions.

Please be informed that this year, there was a fivefold increase in the number of research publications received compared to prior years. As a result, the compilation of two issues with the most outstanding contributions is the product of diligent teamwork. This WIJAR Fall 2023 issue is the first part of the two issues. The subsequent release is scheduled for January 2024, featuring the second cohort of the most remarkable research studies submitted this year.

It is my sincere belief that the accomplishments of this journal are due to the teamwork and shared passion of everybody involved, who have worked tirelessly to explore new avenues of knowledge and bring about meaningful change. We would like to take this opportunity to thank everyone who has helped make our journal what it is today.

The enthusiasm and commitment of the people who write for our journal motivates me. Our publication is driven forward by a dynamic academic community, which includes the authors who submit insightful contributions, the reviewers who carefully assess each submission, and the editorial board members who offer crucial assistance.

Especially, I would like to express my gratitude to Prof. Christa Bixby, former WIJAR Editor-in-Chief, for providing comprehensive guidance and trusting in me and my competence to oversee this research journal. With the same thankful spirit, I would like to sincerely thank Dr. Evelin Suij-Ojeda, Prof. Jodi Crawford and Rachel Sieber, our respected Associate Editors, for their invaluable contributions. Their unwavering commitment to our journal's objective has played a crucial role in molding its course and enhancing its reputation within the academic community. Their remarkable knowledge, thoroughness, and constant support are genuinely priceless contributions to our team.

Finally, I would like to encourage our readers, faculty, students, and researchers in general, to explore the contents of this issue and actively interact with the intellectually stimulating concepts it provides. We are certain that you will consider submitting your research articles to this journal as it is a great resource and a demonstration of the profound impact of academic research.

Sincerely,

Mary Allegra
Editor-in-Chief

ACKNOWLEDGEMENTS

The publishing of the *Westcliff International Journal of Applied Research* (WIJAR) relies on the contributions of dedicated individuals. We extend our appreciation on behalf of the journal to:

- Dr. Anthony Lee for his unwavering support and strong belief in the journal's significant value for Westcliff University and the wider academic community.

- Members of the editorial, internal, and external review boards of WIJAR for participating in the review process to assess and choose high-quality research articles.

- Every author who has dedicated their time and energy to presenting their thoughts and perspectives in this publication.

- The Marketing Department of Westcliff University for their overall participation and contributions to the journal's marketing, the development of the journal’s website, and for their significant role in the publication's success.

- The Westcliff University Writing Center, especially Dr. Holly Eimer, for their assistance and collaboration with the authors who have needed them throughout the revision and review process.

- Dr. Julie Ciancio and Dr. Laura Sliwinski for supporting this project.

- Dr. Jannette Flores and Prof. Christa Bixby, former WIJAR editors-in-chiefs, for their effort and dedication, which have guided the journal’s academic path.

Thank you all!

Factors Influencing Customer Retention and Loyalty in Dental Practice in the United States

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Abstract

This mixed study is an analysis of factors that influence customer retention and loyalty in dental practices in the US. The study determines and encourages patient choice to visit specific dental offices, ensures the well-being of dental customers, and supports the viability of dental practices in the industry. A mixed research methodology was employed, which started with a thematic content analysis of the sampled literature. This produced 18 influencing factors for the dental industry. Afterward, these factors were constructed into survey questions to conduct the primary research via SurveyMonkey and identify dental patient perceptions regarding these 18 factors. Finally, a non-parametric Kruskal-Wallis test was employed to rank and group the 18 factors based on their importance as perceived by US dental patients. The study highlighted the similarities and differences in the influencing factors across extant literature and contemporarily collected data in the US. While the extant literature ranked communication and relation as essential factors in retaining dental patients, the survey prioritized skill and trust as the crucial factors a patient would consider when choosing a dental clinic. This study grouped and ranked all 18 of the identified factors, which any dental clinic could consider retaining and enhancing the loyalty of their existing and prospective clients.

Keywords: Dental practice, customer loyalty, customer retention, Kruskal-Wallis, literature review

Introduction

Background

This study is an assessment of the dental practice business, focusing on factors that promote customer retention and loyalty towards the dental clinic. Identifying the factors that motivate patients to come to dental clinics would be a win-win scenario for both the clinic and the dental patients. Even though owning a private dental practice requires proficient clinical experience and management capabilities as Rehan (2020) claims, there is often no formal education or training in business management at dental schools (Nazir et al., 2018).

The pervasiveness of the internet has made unverified dental practice accessible, in these kinds of practice, patients try alternative treatments to avoid dental visits and attempting treatment on their own, such as whiting tools, retainers, and alignment appliances (Edelstein, 2020). Often, when the case is severe, this can have detrimental impacts on a patient's health. The patients' lack of awareness of evidence-based treatments could be problematic for US oral healthcare. Moreover, in the US, about 124 billion US$ are spent on dental care every year according to Centers for Disease Control and Prevention (2023), and Sikka and Savin (2014) state that the sudden loss of patients may place a financial burden on the clinics, so the dental spending needs to be assessed if it has an impact on the retention. On top of that, Abdelrahman et al. (2021) claim the frequency of dental visits has changed after the Coronavirus (COVID-19) pandemic emerged, and it could be speculated that customer psychology and behavior toward dental visits in the US might have changed compared to the past.

Based on the backgrounds, this study comprised three research questions (RQs):

RQ1: What factors influence customer retention and loyalty in dental practice?

RQ2: Are all factors mentioned in the answer to Research Question 1 equally crucial for clients of dental service providers?

RQ3: If the answer to Research Question 2 is no, what is the ranking of the significance of the factors that influence customer retention and loyalty for clients of dental service providers?

Since RQ1 is qualitative, the study framed the research hypothesis only for RQ2 and RQ3.

Hypothesis for RQ2:

H_0: All factors mentioned in answer to Question 1 are equally important in influencing patient loyalty and retention of dental services.

H_a: There is a disparity among the influences of the factors mentioned in answer to Question 1 about dental service patient loyalty and retention.

Hypothesis for RQ3:

H_0: There exists no significant difference between the factors taken into consideration.

H_1: There exists significant difference between the factors taken into consideration.

Methods and Materials

The study employed a mixed approach, which eliminates research limitation**s** of employing only particular types of tools for data gathering connected to a single research design or combining many studies to achieve an overall goal (Teddlie & Tashakkori, 2009).

Research Design and Method

Aligning to the objectives of RQ1, articles were selected and sorted based on the tag words on which the systematic literature review was conducted, to carry out a thematic content analysis. The analysis enabled the organization and analysis of the literature review, which is difficult to integrate due to the different nature of each article (Williams & Moser, 2019). For RQ2, a survey questionnaire was crafted based on the 18 influencing factors identified in RQ1 and on the researcher's professional expertise as a dentist. The Dental Study Questionnaire (DSQ) designed by Balkaran et al. (2014) and McAlexander et al. (1994) was incorporated into the survey design phase in this study. SurveyMonkey was used to collect responses.

followed by relation, service quality (SQ), trust, facility, perceived value, time management

The responses were collected by using an online portal – 'Survey Monkey". And to make sure the sample represents the attributes of the population, multiple constraints/conditions were kept before collecting the sample, for example, i) the respondent had to have visited the dental clinic at least one time within the last five year, ii) the respondents have to be within the USA, iii) the proportion of gender selected has to be equal. In the process of data collection, the total sample selected for the study was 346, after cleaning the data, 289 were fed in the SPSS for inferential analysis. In the fact Kruskal Wallis test could be conducted when the sample size is small, a sample size of more than 5 is enough for conducting Kruskal-Wallis test (Mugabe et al., 2022).

Following the data collection, a batch Kruskal-Wallis test was employed. This is a non-parametric test used when quantitative research is carried out with ordinal or rank-based data (Gordon, 2022). This test examined if there were any differences among the factors influencing why clients chose certain dental clinics. Ultimately, the presence of differences in RQ2 prompted the researcher to create RQ3 and carry out a more rigorous stepwise Kruskal-Wallis test with an objective of ranking the influencing factors based on responses in the US.

Instrumentation

The thematic content analysis was carried out for the analysis of sampled literature in RQ1 using MS-Excel. The survey questionnaire was designed, and the data was collected through SurveyMonkey for RQ2. A five-point Likert Scale, where a scale of one (1) identifies *strongly disagree* to five (5) *strongly agree*, was provided for the survey. A Statistical Package for the Social Sciences (SPSS) was used to carry out a batch and stepwise Kruskal-Wallis test for RQ2 and RQ3, respectively.

Results

RQ1: Influencing Factors in Dental Practice

Table 1 summarizes the most frequently referenced themes in the sampled papers, along with the names of their authors. There were 32 journal articles from 19 countries, and communication was the most referenced factor,

effectiveness (TimeMgt), empathy, equipment, word of mouth (WOM), professional manner

(ProfMn), skillfulness, treatment gentleness (TxGentl), flexibility of appointment (FlexAppt), cost transparency (Transp), insurance, accessibility, and Social Networking Service (SNS).

Table 1
Influencing Factors Per the Literature Review

S. No	Factors	Number of Articles	Authors
1	Communication	18	American Dental Association, n.d.-a; American Dental Association, n.d.-d; Baldwin & Sohal, 2003; De Lira & Magalhães, 2018; Fujimura, 1995; Geangu et al., 2010; Hamanaka, 2015; Htang, 2019; Ismail & Bader, 2004; Lasadika, 2018; Lee et al., 2014; Matsuda, 2015; McAlexander et al., 1994; McGuigan & Eisner, 2006; Taylor, 2007; Turley, n.d; Ueltschy et al., 2007; Wilson, 2006.
2	Relation	16	Baldwin & Sohal, 2003; De Lira & Magalhães, 2018; Geangu et al., 2010; Gremler & Brown, 1996; Htang, 2019; Lasadika, 2018; Lee et al., 2014; Matsuda, 2015; McAlexander et al., 1994; McGuigan & Eisner, 2006; Royals, 2020; Turley, n.d; Ueltschy et al., 2007; Vargas Perez et al., 2015; Vargas et al., 2012; Wilson, 2006.
3	SQ	12	Baldwin & Sohal, 2003; Geangu et al., 2010; Hashem & Ali, 2019; Htang, 2019; Ismail & Bader, 2004; Köseoğlu & Mutlu, 2019; Lasadika, 2018; Matsuda, 2015; McAlexander et al., 1994; Ueltschy et al., 2007; Vargas Perez et al., 2015; Vargas et al., 2012.
3	Trust	12	Alhidari & Alkadhi, 2018; Fujimura, 1995; Gremler & Brown, 1996; Hamanaka, 2015; Htang, 2019; Ismail & Bader, 2004; Köseoğlu & Mutlu, 2019; Lasadika, 2018; Matsuda, 2015; Turley, n.d; Ueltschy et al., 2007; Vargas et al., 2012.
5	Facility	11	Baldwin & Sohal, 2003; Balkaran et al., 2014; Fujimura, 1995; Hamanaka, 2015; Htang, 2019; Ismail & Bader, 2004; Lasadika, 2018; Matsuda, 2015; Siripipatthanakul & Nyen Vui, 2021; Ueltschy et al., 2007; Wanyonyi et al., 2017.
6	Perceived Value	10	Alhidari & Alkadhi, 2018; Baldwin & Sohal, 2003; De Lira & Magalhães, 2018; Hamanaka, 2015; Htang, 2019; Lasadika, 2018; Linh et al., 2020; Matsuda, 2015; Siripipatthanakul & Nyen Vui, 2021; Taylor, 2007.

6	TimeMgt	10	Baldwin & Sohal, 2003; De Lira & Magalhães, 2018; Fujimura, 1995; Htang, 2019; Lasadika, 2018; Lee et al., 2014; McGuigan & Eisner, 2006; Okuji, 2016; Siripipatthanakul & Nyen Vui, 2021; Turley, n.d.
8	Empathy	9	Baldwin & Sohal, 2003; Hamanaka, 2015; Hashem & Ali, 2019; Ismail & Bader, 2004; Lasadika, 2018; Matsuda, 2015; Ueltschy et al., 2007; Vargas Perez et al., 2015; Vargas et al., 2012.
8	Equipment	9	Baldwin & Sohal, 2003; Fujimura, 1995; Hamanaka, 2015; Htang, 2019; Ismail & Bader, 2004; Lasadika, 2018; Matsuda, 2015. Siripipatthanakul & Nyen Vui, 2021; Ueltschy et al., 2007.
8	WOM	9	Fujimura, 1995; Hamanaka, 2015; Hashem & Ali, 2019; Htang, 2019. Ismail & Bader, 2004; Köseoğlu & Mutlu, 2019; Lasadika, 2018. Matsuda, 2015; McGuigan & Eisner, 2006.
11	ProfMn	7	American Dental Association, n.d.-a; Baldwin & Sohal, 2003; Hamanaka, 2015; Htang, 2019; Matsuda, 2015; Siripipatthanakul & Nyen Vui, 2021; Vargas Perez et al., 2015.
11	Skillfulness	7	Baldwin & Sohal, 2003; Fujimura, 1995; Hamanaka, 2015; Htang, 2019; Matsuda, 2015; Siripipatthanakul & Nyen Vui, 2021; Vargas Perez et al., 2015.
11	TxGentl	7	Baldwin & Sohal, 2003; Fujimura, 1995; Hamanaka, 2015; Htang, 2019; Matsuda, 2015; Siripipatthanakul & Nyen Vui, 2021; Vargas Perez et al., 2015.
14	FlexAppt	6	Baldwin & Sohal, 2003; Htang, 2019; Okuji, 2016; Sharifian & Dean, 2016; Siripipatthanakul & Nyen Vui, 2021; Ueltschy et al., 2007.
15	Transp	5	Alhidari & Alkadhi, 2018; Burger, 2018; Geangu et al., 2010; Okuji, 2016; Turley, n.d.
15	Insurance	5	Burger, 2018; McGuigan & Eisner, 2006; Okuji, 2016; Sharifian & Dean, 2016; Turley, n.d.
17	Accessibility	4	Baldwin & Sohal, 2003; Htang, 2019; Okuji, 2016; Sharifian & Dean, 2016.
18	SNS	3	Alhidari & Alkadhi, 2018; American Dental Association, n.d.-a; De Lira & Magalhães, 2018.

Once the sampled articles were assessed, the researcher generated 18 open codes/themes as the influencing factors. *Table 2* summarizes employed open, axial, and selective code based on thematic content analysis. After generating the influencing factors, the axial code was developed to categorize themes by sorting the shared characters and features of the factors. The 18 themes were then sorted into six groups as nodes in axial code. Finally, selective code was determined and ranked based on the total counts in *Table 2*.

Table 2
Outcome of the Thematic Content Analysis

Nodes	Themes	Individual Reference	Total
Relationship	Relation	16	
	Communication	18	
	Trust	12	
	Empathy	9	55
Internal factors	Facilities	11	
	Equipment	9	
	Accessibility	4	
	FlexAppt	6	
	SQ	12	42
Professionalism	Skillfulness	7	
	ProfMn	7	
	TxGentl	7	
	TimeMgt	10	31
Referral	WOM	9	
	SNS	3	12
Customer's value	Perceived value	10	10
Costs	Transp	5	
	Insurance	5	10

Note. Axial code is derived from the open code.

As illustrated in *Table 2*, the relationship factor had a score of 55, the highest in total sum, based on the cumulative sum in selective code. This indicated that this factor was the most important element among the six groups. However, the scores of internal factors and professionalism, 42 and 31, respectively, were also high. The other three lower factors, referral, customer value, and costs had much lower scores.

RQ2: Are all Factors Equally Important?

Table 3 shows a descriptive analysis of the sample collected through SurveyMonkey. The 18 factors were ordered by the total number of Likert Scale points.

Table 3
Descriptive Analysis

	Mean	Median	Mode	Standard Deviation	Sum
Skillfulness	4.70	5	5	0.59	1358
Trust	4.70	5	5	0.63	1357
Communication	4.47	5	5	0.69	1291
Transp	4.46	5	5	0.71	1289
ProfMn	4.46	5	5	0.67	1289
SQ	4.45	5	5	0.64	1285
Accessibility	4.43	5	5	0.67	1280
TxGentl	4.40	5	5	0.69	1272
Perceived Value	4.39	4	5	0.68	1270
Equipment	4.39	5	5	0.72	1268
Empathy	4.30	4	5	0.78	1244
TimeMgt	4.29	4	4	0.74	1239
FlexAppt	4.25	4	4	0.78	1228
Facility	4.22	4	4	0.71	1220
Insurance	4.14	4	5	0.90	1196
Relation	4.13	4	5	0.95	1195
WOM	3.40	4	4	1.09	984
SNS	2.66	3	3	1.25	768

Table 4 depicts the outcome of the Kruskal-Wallis test. Since the *p*-value is zero, the null hypothesis (H_0) was rejected, inferring that all the 18 factors included in the test were not equally important in influencing customer retention and loyalty to the dental practice.

Table 4
Outcome of the Kruskal-Wallis Test

H_0	Sig.	Decision
All factors are equally important.	.000	Reject H_0.

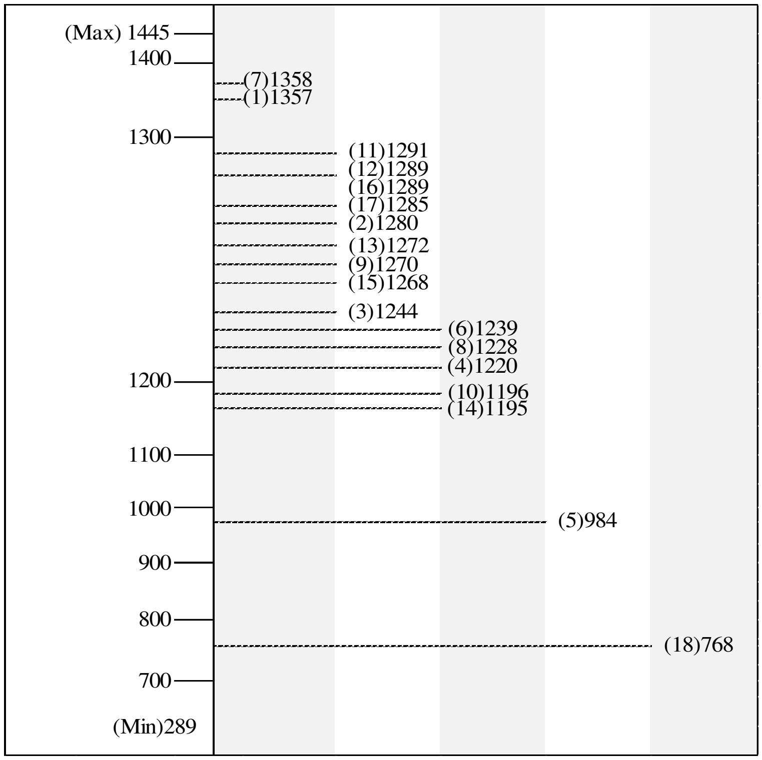
RQ3: Ranking the Influencing Factors

Since the equal importance of sampled influencing factors was rejected in RQ2, further assessment was carried out in RQ3, which focused on the individual prioritization of the elements considered in RQ2.

Analysis of Likert Scale Point

The 18 factors were ranked based on the total sum of the Likert Scale point in *Figure 1*, which was later tested using the Kruskal-Wallis test, and the total sum was derived from the descriptive analysis (Table 3).

Figure 1
Total Likert Point of Each Factor



As shown in *Figure 1*, each factor's total sum of Likert Scale points was recorded into a scale, and the influencing factors were numbered in the scale based on a random order by the researcher for the survey questionnaire provided for RQ2.

Kruskal-Wallis Test Following the Likert Scale Analysis

Following the order on *Figure 1*, a Kruskal-Wallis test was employed again to analyze the numeric significance among the factors. Then the influencing factors were categorized based on their significance values.

Rank 1 and Group 1

First, trust and skillfulness, the highest and second highest factors in the Likert Scale points, were compared via significance value through a Kruskal-Wallis test. The results showed no difference between the two factors since the significance value was 0.914, so H_0 was retained (Table 5).

Table 5
Outcome to Determine Rank 1 and Group 1

H_0	Sig.	Decision
Compared factors are equally important.	.914	Retain H_0.

Following the first comparison, the third influencing factor, communication (11), was added to the two preexisting factors (1 and 7), and a Kruskal-Wallis test was conducted for these three factors. The computation revealed that the significance value was less than 0.001, so there was a statistical difference between them, and H_0 was rejected (Table 6). Therefore, the outcome indicated that trust and skillfulness had the same level of importance, but the third factor (communication) differed from the other two factors (i.e., 1 and 7).

Table 6
Outcome to Distinguish Rank 1 and Group 1

H_0	Sig.	Decision
Compared factors are equally important.	<.001	Reject H_0.

Since communication (11) was confirmed to be significantly different from skillfulness (7) and trust (1), rank 1 as group 1 was generated (Table 7).

Table 7
Summary of Rank 1 and Group 1

S. No	Factor	P-Value	P-Value	Remark	Remark
1	Trust	0.914	0.001	F1=F7	(F1=F7) not equal to F11
7	Skillfulness				
11	Communication				

Rank 2 and Group 2

A new Kruskal-Wallis test was performed where communication was introduced as the opening factor for the second group (since it was observed to be different by the respondents, it was kept in the new group). The researcher continued to compare the third factor (i.e., communication) with the remaining factors (12, 16, 17, 2, 13, 9, 15, and 3), one by one in descending order (Figure 1) and continued adding one more factor to the same group until a difference in significance was observed.

Table 8
Outcome to Determine Rank 2 and Group 2

H_0	Sig.	Decision
Compared factors are equally important.	0.226	Retain H_0.

The test revealed that the significance value for the factors (11), (12), (16), (17), (2), (13), (9), (15), and (3) had the *p*-value of 0.226. Hence, we retained H_0 since no difference in the importance of the factors was perceived by the dental patients (Table 8).

Next, when the twelfth factor, TimeMgt (6), was added to the existing factors (11, 12, 16, 17, 2, 13, 9, 15, and 3), the *p*-value was 0.018, so H_0 was rejected at that point (Table 9). Therefore, since TimeMgt (6) had a different significance, it was introduced again as an opening factor for Group 3 and Rank 3.

Table 9
Outcome to Distinguish Rank 2 and Group 2

H_0	Sig.	Decision
Compared factors are equally important.	.018	Reject H_0.

Since TimeMgt was confirmed to be significantly different from the elements (11, 12, 16, 17, 2, 13, 9, 15, and 3), rank 2 and group 2 was generated, and Table 10 is a summary of the computation process until the significance was met.

Table 10
Summary of Rank 2 and Group 2

S. No	Factor	PV	PV	PV	PV	PV	PV	PV	PV	PV	Rmk	Rmk
11	Comm	0.988									F11 =F12 =F16 =F17 =F2 =F13 =F9 =F15 =F3	(F11 =F12 =F16 =F17= F2 =F13 =F9 =F15 =F3) is not equal to F6
12	Transp		0.95									
16	ProfMn			0.881	0.869							
17	SQ					0.731						
2	Access Tx						0.616	0.621	0.226			
13	Gentl Pcvd									0.018		
9	Value											
15	Equip											
3	Emp											
6	TME											

Rank 3 and Group 3

Again, TimeMgt (6) was kept as an influencing factor for Rank 3 and Group 3. The remaining elements, (8), (4), (10), and (14), continued to be added one at a time until we had a *p*-value higher than 0.05 (Table 11).

Table 11
Outcome to Determine Rank 3 and Group 3

H_0	Sig.	Decision
Compared factors are equally important.	.437	Retain H_0.

Moreover, when WOM (5) was added to the existing group of factors, (6), (8), (4), (10), (14), the *p*-value was observed to be zero (Table 12). Therefore, H_0 was rejected, inferring that WOM met a different level of significance in comparison to (6), (8), (4), (10), and (14). Thus, WOM was kept as the opening factor for Rank 4 and Group 4, and (6), (8), (4), (10), and (14) were categorized into Rank 3 and Group 3. In short, the test confirmed that the seventeenth factor (i.e., WOM) had a different significance than the factors of Group 3, so the factor of WOM was taken as an opening factor for Group 4.

Table 12
Outcome to Distinguish Rank 3 and Group 3

H_0	Sig.	Decision
Compared factors are equally important.	.000	Reject H_0.

Since WOM was confirmed to be significantly different from the elements (6, 8, 4, 10, and 14), rank 3 as group 3 was generated, and Table 13 is a summary of the computation process until the significance was met.

Table 13
Summary of Rank 3 and Group 3

S. No	Factor	P-Value	P-Value	P-Value	P-Value	P-Value	Remark	Remark
6 8 4 10 14 5	TimeMgt FlexAppt. Facility Insurance Relation WOM	0.629	0.473	0.651	0.437	0	F6=F8 =F4=F10 =F14	(F6=F8= F4=F10 =F14) is not equal to F5

Rank 4 and Group 4

Finally, when WOM (5) was kept as an opening factor for the fourth group and SNS (18) was added to it, the results showed that the significance between the two factors was less than zero (0). Since H_0 was rejected (Table 14), the computation demonstrated that the two factors were not equally important for the dental customer.

Table 14
Analysis to Distinguish Rank 4 and Group 4

H_0	Sig.	Decision
Compared factors are equally important.	<.001	Reject H_0.

Thus, from Table 14, we can see that WOM (5) and SNS (18) have different levels of importance in the eye of dental customers. WOM was ranked 4th in Group 4; SNS was ranked 5th in Group 5.

Table 15
Rank and Group of Influencing Factors

Rank (R)Group (G)	Factors
R1G1	(7) Skillfulness (1) Trust (11) Communication (12) Cost Transparency (16) ProfMn (17) SQ
R2G2	(2) Accessibility (13) TxGentl (9) Perceived Value (15) Equipment (3) Empathy (6) TimeMgt (8) FlexAppt
R3G3	(4) Facility (10) Insurance (14) Relation
R4G4	(5) WOM
R5G5	(18) SNS

As shown in **Table 15**, the 18 influencing factors were further classified into five distinct groups with the respective ranking of each group. While the ranking was based on the total Likert point, the grouping was based on the Kruskal-Wallis test. Each of the factors in a group was perceived equally necessary by the respondents; there was no difference among the factors in groups.

Discussion / Implications

Out of the 18 influencing factors identified in RQ1 through the thematic content analysis of extant literatures, relationship which comprised of four influencing factors (relation, communication, trust and empathy) was the highest rank following dental clinic's internal factors which comprised of five influencing factors (facilities, equipment, accessibility, FlexAppt and SQ) as the second. Likewise, the batch Kruskal-Wallis test carried in RQ2 for 18 influencing factors rejected the null hypothesis resulting in an inference that not all of the influencing factors were equally important. Finally, the stepwise Kruskal-Wallis test in RQ3 categorized trust and skillfulness as ranked 1 and group 1 factors, whereas SNS and WOM were ranked as least important by the dental clients. This result reveals a cognitive gap between the understanding of the relevant research articles and customers' expectations regarding the critical factors influencing customer retention and loyalty.

As the outcome of the quantitative research, the actual expectation for skillfulness from customers is still high, and also the importance of that factor as professional competency has been discussed (American Dental Association, n.d.-c). As stated by Alrubaiee and Alkaa'ida (2011), trust from customers was another very crucial factor in the study for the success of medical healthcare business, especially for a small practice business. The SNS and WOM were less important for the respondents when choosing a dental clinic. This implies that customers do not consider these factors as important, which is a slightly different result from the relevant research articles (Alhidari & Alkadhi, 2018).

In comparison with the relevant articles, the study by Alhidari and Alkadhi (2018) had similarities in research direction and stated perceived value and trust as an important factor. Also, while McAlexander et al. (1994) focused on dental service quality, this study has brought 18 influencing factors focusing on a systematic review of dental literature based on the tag words.

Conclusion

This mixed study highlighted the importance of the factors that dental clients would consider before selecting the dental clinics. While the systematic analysis of extant literatures stated 18 crucial factors where communication and the relation between the dental clients and clinics were on the top of the list, the inferential test carried on the same variables concluded that skills of doctors and trust were the prime factors for deciding a dental clinic. The findings from the study will help dental firms focus on the factors that clients think of prime importance while selecting the dental clinics. The perception could further be studied across the different demographic dimensions like their age, income level, education level, and gender.

References

Abdelrahman, H., Atteya, S., Ihab, M., Nyan, M., Maharani, D. A., Rahardjo, A., Shaath, M., Aboalshamat, K., Butool, S., Shamala, A., Baig, L., & Tantawi, M. E. (2021). Dental practice closure during the first wave of COVID-19 and associated professional, practice and structural determinants: a multi-country survey. *BioMed Central Oral Health, 21*(1), 243. https://doi.org/10.1186/s12903-021-01601-4

Alhidari, A. M., & Alkadhi, O. H. (2018). Keep them in: How to drive dental consumers' loyalty in the modern era? *Expert Journal of Marketing, 6*(2), 106-114. https://marketing.expertjournals.com/23446773-612/

Alrubaiee, L., & Alkaa'ida, F. (2011). The mediating effect of patient satisfaction in the patients' perceptions of healthcare quality-patient trust relationship. *International Journal of Marketing Studies, 3*(1), 103-127. https://doi.org/10.5539/ijms.v3n1p103

American Dental Association. (n.d.-a). *How to cultivate loyal dental patients*. https://shorturl.at/grACW

American Dental Association. (n.d.-b). *Practice ownership among dentists continues to decline*. https://shorturl.at/lDGM9

American Dental Association. (n.d.-c). *Preamble*. https://www.ada.org/about/principles/code-of-ethics/preamble

American Dental Association. (n.d.-d). *Your step-by-step guide to a winning customer retention strategy*. https://shorturl.at/kzBDM

Baldwin, A., & Sohal, A. (2003). Service quality factors and outcomes in dental care. *Managing Service Quality: An International Journal, 13*(3), 207-216. https://doi.org/10.1108/09604520310476472

Balkaran, R. L., Osoba, T., & Rafeek, R. (2014). A cross-sectional study of patients' satisfaction with dental care facilities: A survey of adult treatment at the University of the West Indies, School of Dentistry. *The West Indian Medical Journal, 63*(5), 490-498. https://doi.org/10.7727/wimj.2013.197

Burger, D. (2018, July 9). In-office membership plans could build patient loyalty, revenue. *ADA News*, p. 4. https://lscpagepro.mydigitalpublication.com/publication/?m=21718&i=509223&p=4&ver=html5

Centers for Disease Control and Prevention. (2023, September 20). *Oral health conditions*. National Center for Chronic Disease Prevention and Health Promotion, Centers for Disease Control and Prevention. https://www.cdc.gov/oralhealth/conditions/index.html

De Lira, A. D., & Magalhães, B. M. (2018). Digital marketing in dentistry and ethical implications. *Brazilian Dental Science, 21*(2), 237-246. https://doi.org/10.14295/bds.2018.v21i2.1524

Edelstein, B. L. (2020). Disruptive innovations in dentistry. *The Journal of the American Dental Association, 151*(8), 549-552. https://doi.org/10.1016/j.adaj.2020.05.003

Fujimura, K. (1995). Kokyaku no sabisu deribari purosesu eno sanka to hinshitsu hyoka: Iryo sabisu ni okeru gairai oyobi nyuin kanja no hyoka o chushin toshite [Customer participation in the service delivery process and quality assessment: Focusing on outpatient and inpatient assessment in healthcare services]. *The Kagawa University Economic Review*, *68*(1), 119-172.

Geangu, P. I., Gârdan, D. A., Cetină, I., & Gurgu, E. (2010). How the marketing research affects the improvement in the dental doctor-patient relation. *Annals of Spiru Haret University Economic Series, 1*(3), 139-51. https://www.researchgate.net/publication/227489632_How_the_marketing_research_affects_the_improvement_in_the_dental_doctor-patient_relation

Gordon, J. (2022, April 16). *Kruskal Wallis test - Explained*. https://shorturl.at/jBQU0

Gremler, D. D., & Brown, S. W. (1996). Service loyalty: Its nature, importance, and implications. *Advancing Service Quality: A Global Perspective*, *5*(1), 171-180. https://www.researchgate.net/profile/Dwayne-Gremler/publication/242451313_Service_Loyalty_Its_Nature_Importance_and_Implications/links/00b49529e910857e19000000/Service-Loyalty-Its-Nature-Importance-and-Implications.pdf

Hamanaka, T. (2015). *Purofesshonaru sabisu no tai kojin sabisu niokeru kokyaku manzoku kosei yoso no kenkyu [A study of customer satisfaction elements in professional service to individuals].* [Doctoral dissertation, Rikkyo University]. https://rikkyo.repo.nii.ac.jp/records/11563

Hashem, T. N., & Ali, N. N. (2019). The impact of service quality on customer loyalty: A study of dental clinics in Jordan. *International Journal of Medical and Health Research, 5*(1), 65-68. https://rb.gy/tty5do

Htang, E. (2019). *A study of quality of dental care service factors influencing patient satisfaction, trust and loyalty in Yangon, Myanmar.* University of the Thai Chamber of Commerce. https://searchlib.utcc.ac.th/library/onlinethesis/305996.pdf

Ismail, A. I., & Bader, J. D. (2004). Evidence-based dentistry in clinical practice. *The Journal of the American Dental Association, 5*(135), 556-557. https://www.bristolctoralsurgery.com/files/2015/03/EBD-in-clinical-practice.pdf

Köseoğlu, A. R., & Mutlu, H. M. (2019). Corporate image and customer loyalty in the dental health sector. *5th International Conference – ERAZ 2019 – Knowledge Based Sustainable Development* (pp. 41-47). Association of Economists and Managers of the Balkans. https://doi.org/10.31410/ERAZ.2019.41

Kruskal, W. H., & Wallis, W. A. (1952). Use of Ranks in One-Criterion Variance Analysis. *Journal of the American Statistical*

Association, 47(260), 583-621. https://doi.org/10.2307/2280779
Lasadika, M. R. (2018). *The impact of service quality toward customer loyalty through customer satisfaction and trust as a mediating variable (case study R+ & RD Dental Clinic Yogyakarta).* [Doctoral dissertation, Universitas Islam Indonesia]. https://dspace.uii.ac.id/bitstream/handle/123456789/5756/THESIS%20M.RASIS%20LASADIKA%2012311485.pdf?sequence=1&isAllowed=y
Lee, T. R., Huang, M. C., & Hsieh, M. H. (2014). Application of value chain and CRM to dental clinic in business areas. *The Management, Knowledge and Learning International Conference 2014*, 151-163. ToKnowPress. https://www.toknowpress.net/ISBN/978-961-6914-09-3/papers/ML14-496.pdf
Linh, N. T., Nga, D. Q., & Anh, T. D. (2020). Empirical comparision banking service and dental service in using firm resources to enhance customer loyalty. *International Journal of Supply Chain Management*, 9(2), 937-942. https://doi.org/10.59160/ijscm.v9i2.3226
Matsuda, T. (2015). Purofesshonaru sabisu no tai kojin sabisu niokeru sabisu hinshitsu kosei yoso no kenkyu: Shika shinryojo no kanjya manzoku o jirei toshite [A study of formative factors of service quality in professional service for individuals: A case study of patient satisfaction in dental clinics]. *Rikkyo DBA Journal*, 5, 57-76. https://rb.gy/fyunqf
McAlexander, J. H., Kaldenberg, D. O., & Koenig, H. F. (1994). Service quality measurement. *Journal of Health Care Marketing, 14*(3), 34-40. https://pubmed.ncbi.nlm.nih.gov/10138734/
McGuigan, P. J., & Eisner, A. B. (2006). Marketing the dental practice: Eight steps toward success. *The Journal of the American Dental Association, 137*(10), 1426-1433. https://doi.org/10.14219/jada.archive.2006.0056
Mugabe, T., Ndlovu, J., & Zijl, W. V. (2022). Impact of COVID-19 and government imposed lockdown restrictions on South African audit engagements. *Journal of Accounting and Management, 12*(2), 94-104. https://rb.gy/o5lpjx
Nazir, M. A., Izhar, F., Tariq, K., Anjum, K. M., Sohail, Z. B., & Almas, K. (2018). A cross-sectional study of dentists about the need for a practice management course in undergraduate dental program. *European Journal of Dentistry, 12*(04), 508-515. https://doi.org/10.4103/ejd.ejd_184_18
Okuji, M. M. (2016). *Dental benefits and practice management: A guide for successful practices.* Ames: John Wiley & Sons.
Rehan, K. (2020, September 14). *To DSO or not to DSO?* Ontario Academy of General Dentistry. https://agd.org/constituent/news/2020/09/14/to-dso-or-not-to-dso
Royals, K. (2020, January 30). *After 42 years, Imogene Clark still loyal dental school patient*. https://www.umc.edu/news/News_Articles/2020/01/Imogene-Clark-Dental.html
Sharifian, A., & Dean, M. (2016, September 22). *Achieving same-practice growth: A 3-pronged plan*. Dental Economics. https://www.dentaleconomics.com/practice/article/16387998/achieving-samepractice-growth-a-3pronged-plan
Sikka, V., & Savin, G. (2014). *The impact of the financial crisis on the U.S. dental industry*. Dental Economics. https://www.dentaleconomics.com/money/article/16390429/the-impact-of-the-financial-crisis-on-the-us-dental-industry
Siripipatthanakul, S., & Nyen Vui, C. (2021). Dental practice-related factors and patient loyalty in dental clinics, Laem Chabang, Thailand: The mediating role of patient satisfaction. *International Journal of Behavioral Analytics, 1*(2), 1-17. https://ssrn.com/abstract=3943777
Taylor, D. (2007). 8 lessons from corporate America: Building patient loyalty, retention, and referrals. *Dental Economics, 97*(11), 104, 135. https://www.proquest.com/docview/209823532/fulltext/6FF6CA54C0C54325PQ/1?accountid=158986
Teddlie, C., & Tashakkori, A. (2009). *Foundations of mixed methods research: Integrating quantitative and qualitative approaches in the social and behavioral sciences.* Sage.
Turley, R. (n.d). *5 tenets of client retention every hygienist needs to know*. Dentalcareersedu.org. https://www.dentalcareersedu.org/2018/01/5-tenets-of-client-retention-every-hygienist-needs-to-know/

Ueltschy, L. C., Laroche, M., Eggert, A., & Bindl, U. (2007). Service quality and satisfaction: An international comparison of professional services perceptions. *Journal of Services Marketing, 21*(6), 410-423. https://doi.org/10.1108/08876040710818903

Vargas Perez, A. M., Morales Alonso, G., González Fernández, M. C., & Mira McWilliams, J. M. (2015). Components of dental clinic patient loyalty as perceived by the dentist. *The 6th Global Innovation and Knowledge Academy (GIKA) Annual Conference*, 1-24. https://oa.upm.es/42813/1/INVE_MEM_2015_231392.pdf

Vargas, A. M., Martín, M. G., & Idoeta, C. M. (2012). Some insights for a relationship marketing model integrating SERVQUAL and customer loyalty in dental clinics. *6th International Conference on Industrial Engineering and Industrial Management*, 653-660). http://www.adingor.es/congresos/web/uploads/cio/cio2012/EN_09_Information_Systems_and_ICT/653-660.pdf

Wanyonyi, K. L., Radford, D. R., & Gallagher, J. E. (2017). Dental treatment in a state-funded primary dental care facility: Contextual and individual predictors of treatment need? *Plos One, 12*(1), 1-17. https://doi.org/10.1371/journal.pone.0169004

Williams, M., & Moser, T. (2019). The art of coding and thematic exploration in qualitative research. *International Management Review, 15*(1), 45-55. http://www.imrjournal.org/uploads/1/4/2/8/14286482/imr-v15n1art4.pdf

Wilson, C. (2006, December 1). *Technology in tomorrow's dental office.* Oralhealth. https://www.oralhealthgroup.com/featurestechnology-in-tomorrow-s-dental-office/

Improving Project Budgeting Systems by Developing Machine Learning Models

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Abstract

The lack of an efficient budgeting system makes it more difficult for a business to satisfactorily execute projects or gain new business. To improve the accuracy of budgeting using the classical approach, a dynamic system is required. Building dynamic systems that apply machine learning techniques can support companies in improving their budgeting system. This quantitative study built five machine learning regression models: multiple linear regression, artificial neural network, support vector machine, k-nearest neighbors, and random forest. The five built models were used to predict the closing costs of 552 industrial automation projects that were carried out in Africa and the Middle East. Using root mean square error, the model forecast precision was compared to that of the classical system. The outcome shows that there is a significant difference between machine learning models and classical systems. Therefore, the use of machine learning techniques can improve the accuracy for businesses of their budgeting system.

Keywords: Artificial intelligence, machine learning, artificial neural network, support vector machine, random forest, k-nearest neighbors, multiple linear regression, projects, budgeting systems, benchmark

Introduction

The goal of this research project was to examine the potential of machine learning (ML) to improve the way industrial automation projects are budgeted. Companies develop a project budget during the bidding process with the understanding that the expenses will decide the selling price after adding a profit margin. Typically, the time allowed for the bidding process is not enough to accurately forecast future costs. As a result, the project costs may be calculated inaccurately using the existing budgeting system.

It is essential to determine the project budget accurately. Overestimating the selling price could result in missed chances. On the other hand, underestimating the project requirements might result in failing to satisfy clients. Therefore, maintaining business continuity implies the consistent need for an accurate project budget (Eyibio & Daniel, 2020).

The key to long-term corporate success is meeting customers' expectations. Companies may win bids but then without a sufficient budget are not able to fulfill consumers' needs. Contractors may make mistakes when estimating project budgets due to a lack of time during the bidding process. As a result, a quick and accurate budgeting system is required.

The budgeting system should take into consideration the lifecycle of projects and the nature of the industry (Kwon & Kang, 2018). Sophisticated technology initiatives make projects scope more variable. Accordingly, budgeting may not accurately respond to rapidly changing projects (Miandoab & Gharehchopogh, 2016).

Additionally, every project is unique in terms of timeframe, scope, risks, and other aspects. Although complex projects enhance the reputations of businesses, there is a significant risk that they may run over budget or behind schedule (Browning, 2019). Generally, projects are not completely defined during the initial phase. During the project execution, additional charges might be incurred. Businesses pursue minimizing the gap between the initial budget and the closing cost. Therefore, the budgeting process should consider the different aspects of a project, including a project timeframe, scope of work, market circumstances, and project complexity.

This research addresses a business need for many companies to enhance their ability to win projects with high customers' satisfaction. Unfortunately, there is not much research in using machine learning in the industrial automation budgeting system. The complexity and uniqueness of the industrial automation projects makes it difficult for companies to create a budgeting benchmark using the classical system. Therefore, this research utilizes machine learning techniques to cover this gap.

In the classical approach, the scope of work is divided into small tasks called a work breakdown structure (WBS) (Devi & Reddy, 2012). The project evaluates the adequate resources required to complete the WBS (Cerezo-narv et al., 2020). The basis of the estimate should include material, labor, freight, taxes, currency exchange, cost of finance and any other costs associated with the project execution (Greco, 2018). Fundamentally, material and engineering are a project two main cost components. For example, materials account for more than half of the project costs for the construction businesses (Mahagaonkar & Kelkar, 2017). All logistics activities, including shipping, transportation, and customs clearance, should be considered in the budget.

Initially, the project scope may not be precisely defined. Therefore, businesses may produce estimates of an opening budget (Srinivasan et al., 2021). During the project execution phase, a final solution is developed and submitted along with the final bill of material. Consequently, additional materials may be required to complete the technical solution and ensure that the system functions correctly.

According to a statistical analysis conducted in Hong Kong with a sample of projects with contracts value USD 14 billion, 47% of projects deviated from the planned budget (Love et al., 2019). Therefore, the budget should reserve an amount for risks and contingencies. Project management information systems can help with the risk quantification to be included in the budget (Besouw & Bond-Barnard, 2021).

Given the limits of the classical bidding process, ML regression helps to increase the accuracy of the budgeting system. ML models create a nonlinear link between dependent and independent variables (Antunes et al., 2021).ML provides regression models that may improve the precision of the budgeting system without going into the time-consuming classical method. ML uses data and algorithms to mimic the human brain to improve forecasting accuracy. ML technology is used in many fields: pattern recognition, medical applications, risk assessment, finance, and entertainment (El Naqa, 2015).

ML is classified as supervised, unsupervised, and reinforcement learning. Supervised techniques build algorithms from existing cases to automate decision-making (Burkart & Huber, 2021). The supervised learning technique develops prediction models by learning from many training instances, each containing a label identifying the output (Zhou, 2018).

Regression models use independent variables as inputs to forecast a project budget. ML techniques apply various types of regression: multiple linear regression (MLR), artificial neural network (ANN), support vector regression (SVR), k-nearest neighbor (KNN), and random forest (RF). These ML regression models may perform better than the classical budgeting method.

The different regression models draw a connection between cost factors and the projected budget. The ANN technique is highly effective in developing a mathematical equation used in predicting costs (Abd & Naseef, 2019; Balali et al., 2020; Tijanić et al., 2020). Among ML methods, the ANN and SVM techniques yield excellent estimation results (Hassim et al., 2018; Mohammed et al., 2021)

Additionally, ML can build a benchmark for future projects to increase computation speed as well as improving precision. A comparison of the classical and ML methodologies was done in order to evaluate the efficacy of the recently developed ML models.

Methods and Materials

The research entails developing ML models to forecast the project overall cost. The cost categories were regarded as the models input or independent variables. The actual project cost was regarded as the dependent variable.

The cost categories were considered as independent variables of the models. Under each cost category, there were expense items that stated the cost incurred under each item. The cost categories are hardware, engineering, logistics, cost of finance, risks, installation, and others. The dependent variable was calculated based on the aggregation of all actual cost items of each associated project. The initial budget of cost items was compared with the actual project cost upon closure of the sample projects to determine the actual budget error.

The initial budget and the actual cost were extracted from secondary data. Typically, businesses record the budget of projects on a project management information system (PMIS). Throughout the course of the project, the budget gets revised. Based on the project execution circumstances, some budget amounts can be moved from one cost center to another. In some cases, an additional budget is required to complete the project.

The secondary data were split into 70% for training and 30% for testing. The ML regression models used the project training data to update their algorithms. Consequently, the testing data set was used to verify the efficiency of the ML prediction models. Each ML regression model efficiency was compared with the actual budget error to determine which model provided the most accurate prediction.

The population of the secondary data consisted of industrial automation projects that had been completed during the previous 5 years. The sample was gathered from completed and closed projects that were received from 552 projects executed in five different countries. Every project differed in terms of its scale, schedule, stakeholder requirements, and environmental restrictions. However, the life cycle, engineering, logistics, and funding of projects were comparable.

The information extracted from the PMIS included both the initial budget for cost categories as well as the actual expenses that had already been incurred to complete the projects. The ultimate cost was used as the dependent variable to develop the ML models. The cost categories, including material, engineering, logistics, finance, risks, services, overheads, installation, and others, are considered the independent variables in the regression models.

Each cost category included sub sectors that are called cost centers. The cost centers were aggregated to comprise the cost categories. The data were extracted from the PMIS in transactional formats. Therefore, the data were validated and reshaped to be imported in the ML software. The regression models were developed using the R language to build the ML regression models: MLR, ANN, SVR, KNN, and RF.

Because the data contained information from different executed projects, the cost categories had different scales. For instance, the hardware budget could be given more consideration in one project than the logistical budget. Considering this, data preprocessing is crucial for enhancing ML performance. Scaling the various characteristics helped the models to run faster and perform better.

In a dataset, the information from several projects was kept as 30% of the dataset for testing, while 70% was used for training. The data of testing and training datasets were selected on a random basis from the secondary data. The algorithms developed independent variable weight using the training data. The performance of the models was evaluated using the root mean square error (RMSE) between the forecasted budgets and the actual costs listed in the testing datasets.

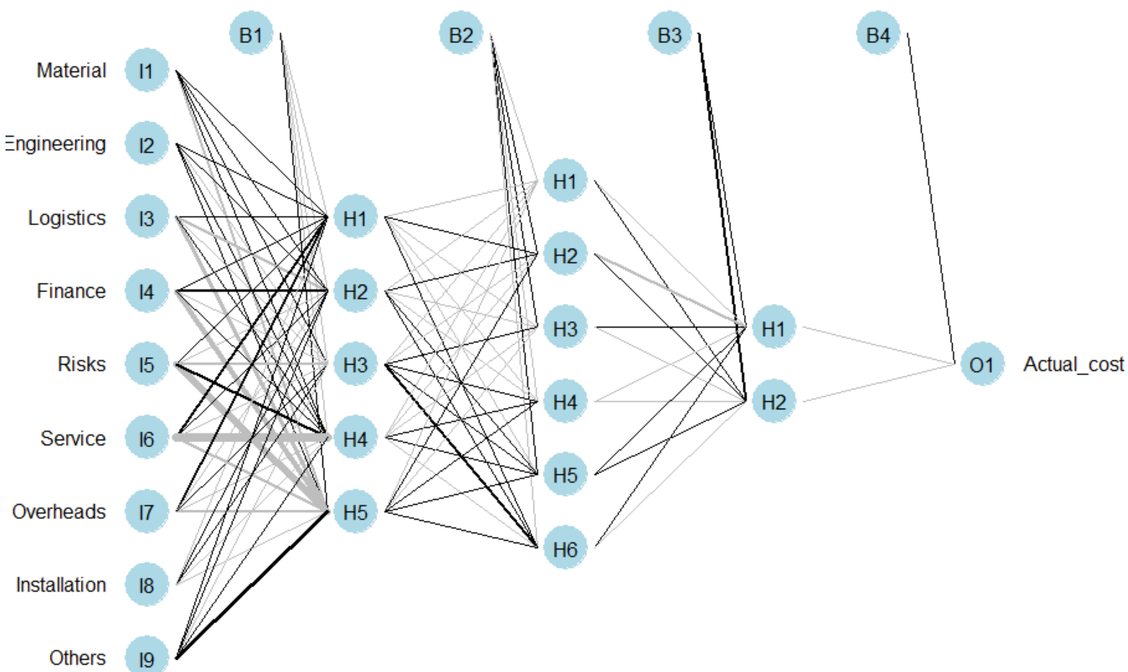
Data preprocessing is the next step in the modelling process after importing the data into R-Studio. The data were scaled. The code developed five groups of the regression models, MLR, ANN, SVR, KNN, and RF models. The code trained the models using different R-libraries, and then listed the regression outputs in a matrix for comparison. The optimal configurations of the regression models were determined by a tuning grid or nested loops. Accordingly, the forecast was created for each model using the testing dataset. The RMSE between the forecasted budget and the actual cost was calculated and listed in a matrix for comparison.

ANN models had been created using a variety of techniques. Model_ANN1 is run with just one hidden layer using the default settings. Two more ANN models were created and tuned using nested loops to determine the best fit to the training and the testing datasets. Model_ANN_Train showed the minimum RMSE between the training dataset and the actual cost. Nevertheless, the RMSE of the testing dataset of the model Model_ANN_Train showed a sign of overfitting. In other words, the Model_ANN_Train showed high ability to fit to the training dataset, however, it showed low generalizability performance.

In order to consider the generalizability, Model_ANN_Test was created and tuned to fit with the testing dataset. Figure 1 shows the configuration of Model_ANN_Test. The Caret library was used to develop ANN model called Model_Caret_ANN1. The H2O library for deep learning, a subset of the neural network, was used to create an ANN model called Model_H2O_DEEP1.

Figure 2

Artificial Neural Network Model



Note. The graph shows ANN with three hidden layers with neurons (5, 6, 2).

The support vector regression models were created. Model_SVM1 was built using E1071 library. Model_Caret_SVM1 and Model_Caret_SVM2 were created by the Caret library using svmRadial and svmLinear methods respectively.

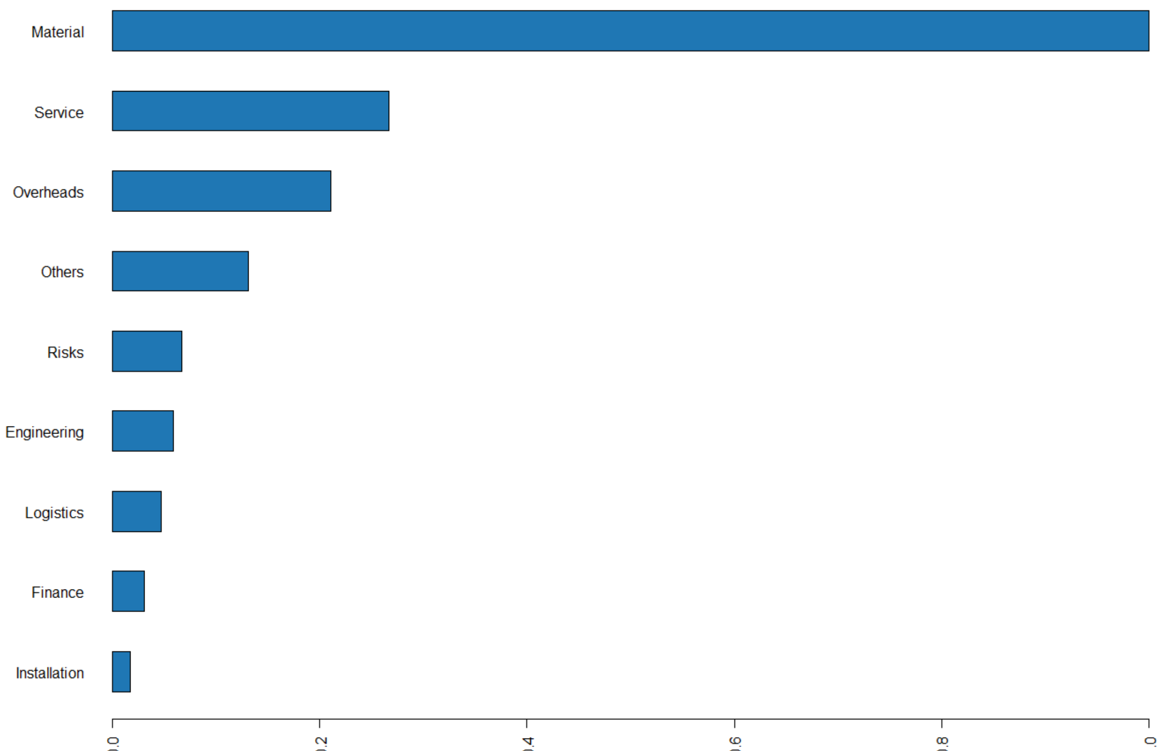
KNN models were created using different libraries. Model_KNN1 has five nearest neighbors in the regression model configuration. Caret library was used to develop Model_Caret_KNN1 and Model_Caret_KNN2. Model_Caret_KNN1 demonstrated higher precision in fitting the model to the training dataset. On the other hand, Model_KNN1 demonstrated a higher generalization competence.

Random forest regression models, Model_RF1, Model_Caret_RF1, and Model_H2O_RF1, were created using libraries Caret, Random Forest, and H2O respectively. Model_Caret_RF2 was created using a quantile random forest. The code showed similar accuracy between Model_RF1 and Model_Caret_RF1 as advantageous for extrapolation and fitting the training dataset.

The algorithm determined the importance of the variables to specify the most critical variables that contributed to the prediction. A budget system should concentrate on variables of the highest importance. In contrast, the less important variables may consume less time while preparing the budget. Given that bidding phases are time-limited, concentrating on the most important cost categories may be advantageous using the variable significance map. The map of variable importance of the model Model_H2O_RF1 is shown in Figure 2. According to the model, the most significant independent variables were material, service, and overheads.

Figure 3

Importance of Independent Variables



Note. Model_H2O_RF1 shows the importance of the independent variables.

Results

As discussed, five groups of regression models were created. Consequently, the RMSE between the forecasted budget and actual costs were calculated for both training and testing datasets. The RMSE were calculated for all models along with the real data to assess the performance of the models. The actual RMSE indicates the discrepancy between actual and budgeted expenditures while using the classical budgeting technique. Table 1 displays the RMSE of the models considering training and testing datasets.

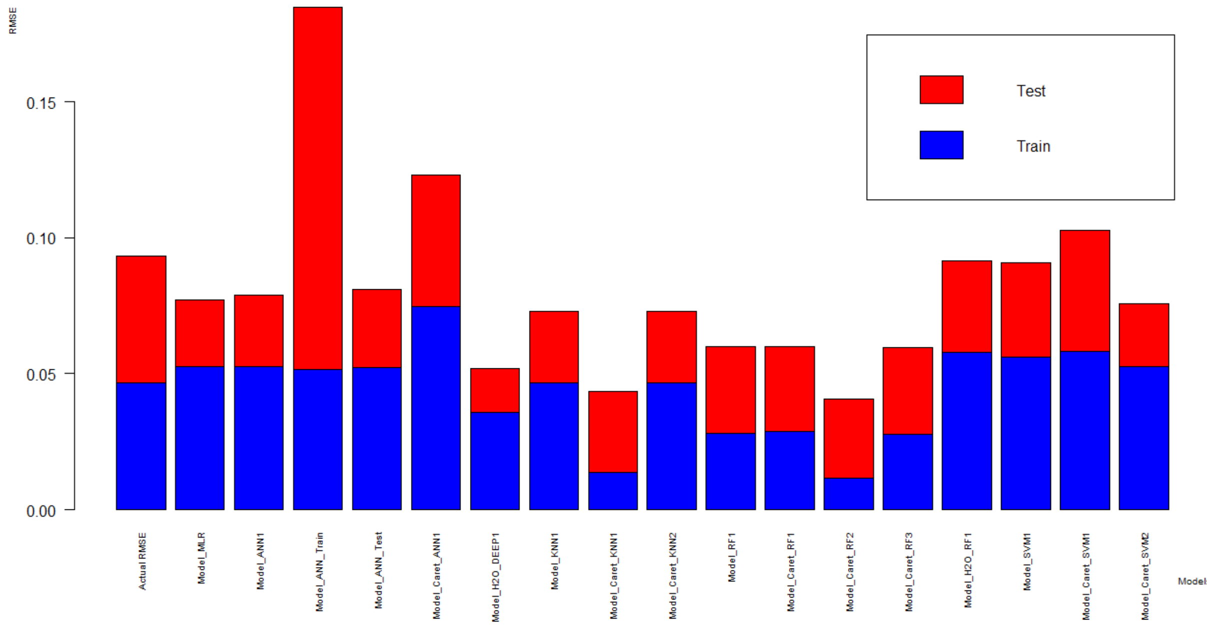
The table shows models with high prediction accuracy. Model_Caret_RF2 and Model_Caret_KNN1 showed high ability to fit with the training dataset. Model_ANN_Train showed overfitting to the training dataset. Model_H2O_DEEP1, Model_ANN_Test, and Model_Caret_RF2 showed high generalizability.

Table 16
Models RMSE

Model Name	Train RMSE	Test RMSE
Actual RMSE	0.046561753	0.046561753
Model_MLR	0.052411622	0.024788497
Model_ANN1	0.052560323	0.026308781
Model_ANN_Train	0.051655975	0.133026625
Model_ANN_Test	0.052399354	0.028609701
Model_Caret_ANN1	0.074509863	0.048495304
Model_H2O_DEEP1	0.035644294	0.016213948
Model_KNN1	0.046456911	0.026537751
Model_Caret_KNN1	0.013591195	0.030051811
Model_Caret_KNN2	0.046456911	0.026537751
Model_RF1	0.028033991	0.031779313
Model_Caret_RF1	0.028893984	0.031152761
Model_Caret_RF2	0.011702676	0.029131458
Model_Caret_RF3	0.027786526	0.031934766
Model_H2O_RF1	0.058015196	0.033510511
Model_SVM1	0.056112486	0.034586428
Model_Caret_SVM1	0.058096735	0.044510994
Model_Caret_SVM2	0.052615943	0.02294875

Figure 3 displays the comparison of the ML models RMSE. Each model RMSE is depicted on the Y axis. The training and testing RMSE are denoted by the colors blue and red, respectively.

Figure 4
RMSE Statistical Test and the Results



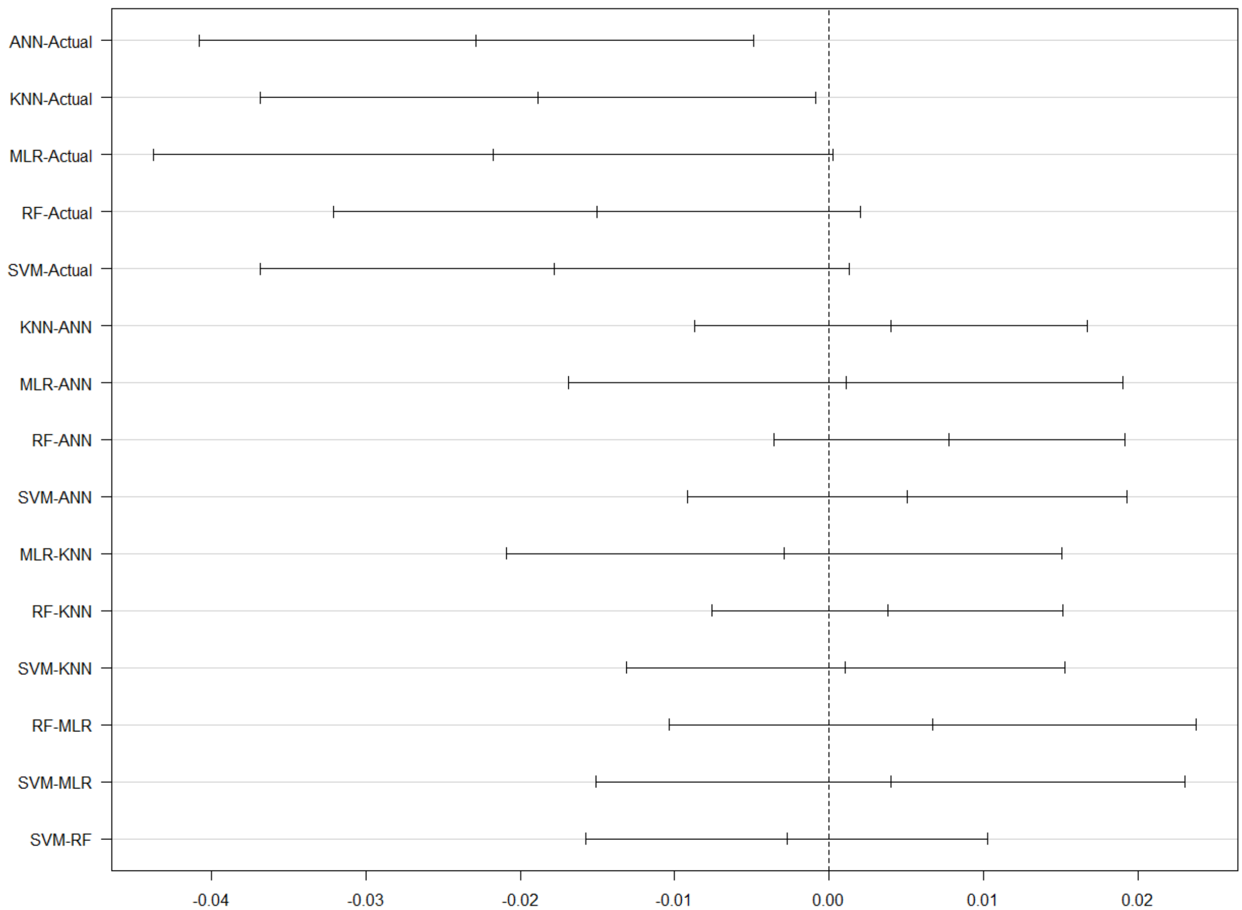
The models were aggregated into five groups: MLR, ANN, SVR, KNN, and RF to be compared with the actual RMSE. The actual RMSE is the error between the classical budgeting system and the actual cost. An ANOVA test was conducted to compare the variance across the mean of the five groups. An analysis of variance yielded significant variation among the ML models and the classical budgeting system. Table 2 presents the outcomes of the ANOVA test. The test revealed a significant difference between the ML RMSE and the actual RMSE.

Table 17
Analysis of Variance Test Result

	df	Sum Sq	Mean Sq	F value	Pr(>F)
Model	5	0.0004443	8.887e-05	4.625	0.0229*
Residuals	9	0.0001729	1.922e-05		

A Tukey post hoc test was conducted to specify which model showed the significant difference with the actual RMSE. Figure 4 presents the findings. According to the test results, ANNs and KNN showed significant differences with the classical budgeting system.

Figure 5
Tukey Honestly Significant Difference Post Hoc Test



Note. 95% family-wise confidence interval.

Discussion / Implications

The results of the variance analysis show a significant difference between the ML models and the classical budgeting system. The findings disclose a significant variance between the actual RMSE and the ML RMSE with $F(5, 9) = 4.625$, $p < 0.05$. The results of a post-hoc Tukey test reveals that ANN and KNN models show a significant difference with the classical budgeting system with $p < 0.05$.

In conclusion, the precision and efficiency of budgeting systems can be improved by ML approaches. The Caret library RF performed best in terms of accurately fitting the model to the training dataset. The deep learning model developed by H2O library showed the best generalization accuracy.

The outcomes show that ML may enhance the budgeting process. The gap between the budget and actual costs may be reduced using ML models. As a result, businesses may improve their chances of winning projects without bearing a significant risk of going over budget. Using previous data, the ML models may provide a more precise projection of a project cost. Consequently, businesses may provide budgetary offers with minimum effort. Moreover, managers may validate the prices offered to the clients and highlight if there is an enormous discrepancy between their estimated cost and the anticipated.

Additionally, the algorithm specifies the weightages of the cost categories. Therefore, businesses may concentrate on the important elements affecting the budget. Hence the companies may prepare the budget more quickly without jeopardizing the budget accuracy. The least important factors can be estimated as a percentage of the most critical factors.

Companies can use ML models to create a benchmark. A company can specify a near estimate of a project using the ML models without going into detail by using prior project data. Companies may save time and effort when creating the cost estimate by offering a baseline. Conversely, the benchmark created by the ML model may indicate when the budget is overstated or undervalued.

In summary, businesses can benefit from their cumulative knowledge gained from executing projects in providing information to the ML model. This research supports companies in turning project lessons learned into quantified information to develop a machine learning model to adjust their pricing and costing system to win competitions. By analyzing business historical data, the model can support real-time decision-making in terms of pricing. Moreover, by using information collected from competitor pricing at open bids, the model can identify competitor pricing patterns. Accordingly, companies can predict the winning price.

This research provides an approach to develop project budgeting using ML techniques. ML can be utilized to provide a model to estimate the real cost. Each company may have different cost categories that regression models can accommodate. Additionally, the research offers a methodology for evaluating each model accuracy and comparing it with the actual error using RMSE to conclude which ML model best fits the company's nature of business.

Using previous data, companies can develop project benchmarks. Scientifically, accurate ML models are primarily dependent on reliable data and precise cost allocation. In this study, ANN and KNN demonstrated the most significance. In other businesses, the model may be different. Nevertheless, the concept still applies.

Many different sectors can benefit from the ML methodology outlined in the research. To do this, businesses should employ a project management information system to record precise historical data for the development of ML benchmarking models. In addition to large businesses, small and medium-sized businesses can develop their own ML models using the data developed on their systems. Although the benchmark of one company cannot be used for another, it provides a reliable estimate of the project market pricing.

This research used a limited sample of 552 projects to build the ML models. Accordingly, the models can be reproduced with more information from businesses in various regions. Additionally, this study utilized the field of industrial automation. The study can be expanded to include additional industries and different cost categories. Moreover, research can examine whether eliminating the least important expense categories compromises the accuracy of predictions.

The relationship between the expense categories is exceedingly important for businesses. For instance, demonstrating that logistics require a certain percentage of materials cost would enable companies to prepare budgets more quickly. As a result, creating a relationship between cost categories offers a research opportunity.

Consequently, the approach of using ML to forecast the actual cost can be applied to each cost category. Therefore, the independent variables can be transferred to be dependent variables. For instance, in the industrial automation field, it is possible to estimate the number of engineering hours by creating an ML model that includes engineering factors such as the number of input/output points, graphic pages, and hardware cabinets. Likewise, the cost of installation could be determined as a factor of site conditions, the hardware, and engineering hours.

Conclusion

Machine learning models reveal significant differences in forecasting the actual cost compared to the classical budgeting system. Machine learning techniques can be used to provide an estimate for project actual cost. Although different cost categories may be used, businesses can utilize the same methodology to conclude the machine learning model that best fits with their sector. RMSE can be used to assess the accuracy of machine learning prediction compared to the classical budgeting system. Therefore, companies may benefit from machine learning models to predict the final project cost to improve the budgeting system.

References

Abd, A. M., & Naseef, F. S. (2019). Predicting the final cost of Iraqi construction project using artificial neural network (ANN). *Indian Journal of Science and Technology*, *12*(28), 1-7. https://doi.org/10.17485/ijst/2019/v12i28/145640

Antunes, E., Vuppaladadiyam, A.K., Sarmah, A.K., Varsha S. S. V. , KishorePant, K., Tiwari, B., & Pandey, A. (2021). Application of biochar for emerging contaminant mitigation, *Environmental Management and Protection* (pp. 65–91). https://doi.org/10.1016/bs.apmp.2021.08.003

Balali, A., Valipour, A., Antucheviciene, J., & Šaparauskas, J. (2020). Improving the results of the earned value management technique using artificial neural networks in construction projects. *Symmetry*, *12*(10) , 1-16. https://doi.org/10.3390/sym12101745

Besouw, J. Van, & Bond-Barnard, T. (2021). Smart project management information systems (SPMIS) for engineering projects. *Project Performance Monitoring & Reporting*, *9*(1), 78-97. https://doi.org/10.12821/ijispm090104

Browning, T. R. (2019). Planning, tracking, and reducing a complex project's value at risk. *Project Management Journal*, *50*(1), 71-85. https://doi.org/10.1177/8756972818810967

Burkart, N., & Huber, M. F. (2021). A survey on the explainability of supervised machine learning. *Journal of Artificial Intelligence Research*, *70*, 245-317. https://doi.org/10.1613/JAIR.1.12228

Cerezo-Narv, A., Pastor-Fernández, A., Otero-Mateo, M., & Ballesteros-Pérez, P. (2020). Integration of cost and work breakdown structures in the management of construction projects. *Applied Sciences*, *10*(4), 1-33. https://doi.org/10.3390/app10041386

Devi, T. R., & Reddy, V. S. (2012). Work breakdown structure of the project. *International Journal of Engineering Research and Applications*, *2*(2), 683-686.

El Naqa, I. (2015). Detection and prediction of radiotherapy errors. *Machine Learning in Radiation Oncology: Theory and Applications*, 237-241. https://doi.org/10.1007/978-3-319-18305-3

Eyibio, O. N., & Daniel, C. O. (2020). Effective resource budgeting as a tool for project management. *Asian Journal of Business and Management*, *8*(2), 15-20. http://doi.org/10.24203/ajbm.v8i2.6190

Greco, A. (2018). *Direct costs vs indirect costs*. Project Cubicle. https://www.projectcubicle.com/direct-costs-and-indirect-costs-cost-classification/

Hassim, S., Muniandy, R., Alias, A. H., & Abdullah, P. (2018). Construction tender price estimation standardization (TPES) in Malaysia: Modeling using fuzzy neural network. *Engineering, Construction and Architectural Management*, *25*(3), 443-457. https://doi.org/10.1108/ECAM-09-2016-0215

Kwon, H., & Kang, C. W. (2018). Improving project budget estimation accuracy and precision by analyzing reserves for both identified and unidentified risks. *Project Management Journal*, *50*(1), 86-100. https://doi.org/10.1177/8756972818810963

Love, P. E., Sing, M. C., Ika, L. A., & Newton, S. (2019). The cost performance of transportation projects: The fallacy of the Planning Fallacy account. *Transportation Research Part A: Policy and Practice, 122*, 1-20. https://doi.org/10.1016/j.tra.2019.02.004

Mahagaonkar, S. S., & Kelkar, A. A. (2017). Application of ABC analysis for material management of a residential building. *International Research Journal of Engineering and Technology*, *4*(8), 614-620.

Miandoab, E. E., & Gharehchopogh, F. S. (2016). A novel hybrid algorithm for software cost estimation based on cuckoo optimization and k-nearest neighbors algorithms. *Engineering, Technology & Applied Science Research*, *6*(3), 1018-1022. https://doi.org/10.48084/etasr.701

Mohammed, S. J., Abdel-Khaled, H. A., & Hafez, S. M. (2021). Predicting performance measurement of residential buildings using machine intelligence techniques (MLR, ANN, and SVM). *Iranian Journal of Science and Technology - Transactions of Civil Engineering*. *46*, 3429–3451. https://doi.org/10.1007/s40996-021-00742-4

Srinivasan, N. P., Gowtham, T., Kumar, A. R. R., Baalaji, M., & Kumar, S. N. (2021). A review on feasible cost prediction model in construction projects. *Information Technology in Industry*, *9*(3), 537-543.

Tijanić, K., Car-Pušić, D., & Šperac, M. (2020). Cost estimation in road construction using artificial neural network. *Neural Computing and Applications*, *32*(13), 9343-9355. https://doi.org/10.1007/s00521-019-04443-y

Zhou, Z. (2018). A brief introduction to weakly supervised learning. *National Science Review*, *5*(1), 44-53. https://doi.org/10.1093/nsr/nwx106

Factors Influencing Real Estate Purchasing in Dubai

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Abstract

Identifying the factors affecting real estate purchasing is globally crucial to the industry stakeholders. The researcher noticed a lack of literature that defines and explains the factors influencing the expatriates' Intention to purchase residential properties in Dubai. In this quantitative study, the researcher utilized the theory of planned Behavior (TPB) to investigate the effect of attitude, subjective norms, and perceived behavior controls on the Intention to purchase residential real estate properties. Based on 384 usable responses received through randomly distributed survey questionnaires. All three research alternative hypotheses were found to be accepted. The empirical results show positive relationships between attitude, subjective norms, and perceived behavior control toward real estate property purchasing intention.

Keywords: Consumer behavior, behavioral intention, human planned behavior, Dubai real estate, Dubai properties, real estate purchasing, theory of planned behavior (TPB), residential properties

Introduction

Although purchasing a residential property can be a beneficial investment rather than renting it for a long duration of an expatriate's stay in Dubai, the expatriates prefer renting rather than investing the same amount of money in purchasing properties in mortgage plans. Interestingly, expatriate families spent on average 44% of their annual income on accommodation rent and utility bills according to Dubai Statistics Center (2014, 2015, 2021a). Moreover, the expatriates prefer to send their cash surplus to their home countries (Bridge, 2018), which has negatively influenced the UAE economy (Carvalho, 2005; Central Bank, 2020). The significance of the research problem becomes noticeable when comparing the number of rented-out residential properties of 405,000 lease contracts according to the Dubai Land Department (2022) and the number of households in Dubai of 598,870 families (Dubai Statistics Center, 2020).

Some interesting initial search findings that may be contrary to this prevailing condition are first, Dubai's real estate (RE) market has proven to be one of the fastest growing and highest yielding RE investments in the Middle East region as of 2022 (Dubai Land Department, 2020; “Dubai real estate", 2022; Lejeune et al., 2021). Also, it is worth mentioning that the real estate markets globally have witnessed several fluctuations in demand during the last decade due to several global economic recessions, the COVID-19 pandemic, the Russian-Ukrainian war, and other unpredicted events, however, the demand for purchasing Dubai properties remained steady (Abbas, 2018a; Fattah et al., 2022 & Turak, 2023). Also, in the early 2000s, the government allowed expatriates of all nationals to buy and sell RE properties on freehold ownership. Also, foreigners who do not reside in the country and residents are eligible to gain unrestricted ownership freehold rights, usufruct rights, or property leaseholds according to information provided by The United Arab Emirates' Government (UAE, 2021). Finally, expatriates in Dubai earn better than others in other major global cities and hold the privilege of no taxation on income in the UAE (Abbas, 2018b). Despite all these facts that clarify the ease with which expatriates can purchase RE, it was found that it is not positively reflected in the demand for RE purchases in Dubai by the expatriates.

The researcher noticed a lack of identification of the factors influencing the expatriates' intentions to buy residential properties in Dubai, and it was evident that no academic studies investigated such factors.

Understanding such factors will help RE industry professionals and policymakers improve their strategies and explore new business opportunities. Therefore, the purpose of this quantitative study is to identify the factors influencing expatriates' purchasing intention for residential property in Dubai.

Literature Review

Through literature review, the researcher investigated the relevant RE prevalent information concerning the expatriates, ranging from their demography, income, financial capability, spending, and living conditions. Also, the researcher investigated the significance and importance of Dubai's RE market in the UAE economy. Finally, the researcher conducted a literature review for similar scope studies and searched for applicable theoretical frameworks that could guide this research.

Expatriates in Dubai and the RE market

In 2021, the number of UAE expatriates was 8.84 million, representing 89% of the total population and more than 90% of the country's workforce. More than 80% of Dubai's workforce are expatriates (Dubai Statistics Center, 2022; Kumar, 2018; “More than”; 2021). The gender ratio in Dubai was 69% male to 31% female (Dubai Statistics Center, 2021d; Forstenlechner & Rutledge, 2011), presumably due to many males leaving their families behind and staying alone in Dubai due to the high living expenses (Swan, 2017). Expatriates' stay in the country is conditioned by maintaining a valid employment contract, investment visa, or long-term golden visa for specific qualification individuals, and real estate investors (Ali, 2011; Cave, 2004; The United Arab Emirates' Government, 2022a). An expatriate family's average annual household expenditure in Dubai is approximately AED 206,000 —USD 56,300 (Dubai Statistics Center, 2021a).

While the amount spent on a property rent over a 15–20-year is equivalent to investing the same amount in purchasing the same property in a mortgage plan in the same duration, a 2020 survey found that 75% of the expatriate participants were not able to save for their retirement in UAE; while half of them rely on end-of-service gratuity (Bell, 2011; Sawy, 2020). Meanwhile, the volume of their remittances was AED 154 billion or USD 42 billion in 2020, which had a negative impact on the local economy and the GDP of the UAE (Carvahalo, 2005; Central Bank, 2020).

When looking at the RE market in Dubai, the government recorded about 735,559 residential units in the emirate, where apartments and villas make up 96%. Other accommodation types, such as villa attachments, collective households, and traditional Arabic houses together are the remaining 4%. Out of the total available residential units, apartments represent 79% of units, while villas represent about 17% (Dubai Statistics Center, 2020).

There are several categories of buyers, mainly Emirati nationals, expatriate investors, expatriates who buy for their personal use, international investors, and retirees (The United Arab Emirates’ Government, 2022b). Typically, the majority of RE buyers are older and middle-aged, above 35 years old (Bridge, 2019; "Getting on the property", 2022; Nair, 2018).

Meanwhile, it was recognized that Dubai's RE market is continuously improving and carried out 84,196 sale transactions with a total amount exceeding AED 300 billion in 2021 alone —the highest number of transactions ever recorded in Dubai's RE history, thanks to the increasingly appealing payment plans and lower home costs (Dubai Land Department, 2023). This is an outcome of the UAE making it possible for a wide variety of interested buyers to become purchasers of RE properties, allowing expatriates of all nationals to buy and sell RE properties on freehold ownership. The government is continuously refining the laws and regulations of RE purchasing to increase property purchasing frequency and potential buyer numbers through investment prospects to enhance the economy (The United Arab Emirates’ Government, 2022b).

Additionally, economy specialists have provided that fostering demand for RE purchasing can play a substantial part in raising the UAE economy's non-oil GDP due to the RE industry being one of four major contributors to the Dubai economy (Central Bank, 2020; Dubai Land Department, 2020; Dubai Land Department, 2022; Lejeune et al., 2021).

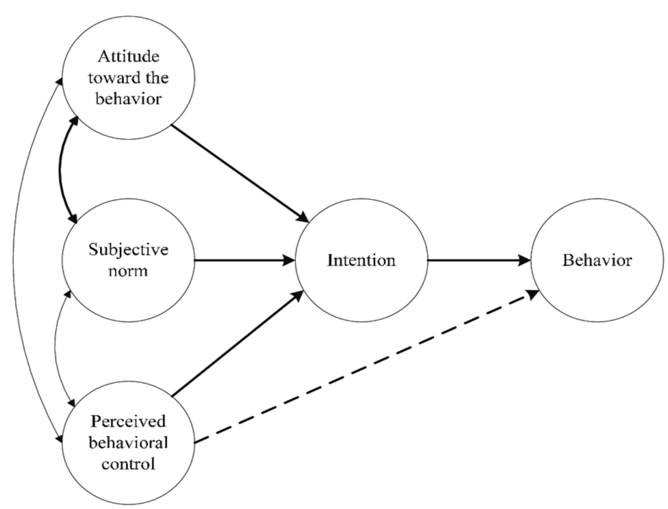
The RE sector is one of four major components of the economy of Dubai. Also, the RE and Construction industry came in first with the highest number of employments at a significant weight of 22% or about 664 thousand workers out of 2.9 million employees in Dubai. Also, it came second with a 13.2% contribution to Dubai's GDP in 2020 compared to the retail and wholesale sector, which leads in first with a 24.2 % contribution to the Dubai 2020 GDP (Dubai Statistics Center, 2021b; 2021c).

Theory of Planned Behavior (TPB)

The TPB of Ajzen is one of the most acknowledged and well-recognized theories in the field of human behavior, reaching about 5 million hits of relevant academic works and studies on a Google Scholar search in January of 2023. Several studies such as Hrubes et al. (2001), Knabe (2012), Gopi & Ramayah (2007), Tan (2013), and Montano & Kasprzyk (2008) have concluded empirical evidence that supported the validity of the theory in different domains. In this research, the TPB of Ajzen (1991) was adopted for being a widely recognized theory in the field of behavioral change and for being a theory that works on both a psychological and socio-psychological level, as Boonroungrut and Huang (2020) suggest.

The TPB proposes that intentions to engage in activities can be predicted to a high degree of accuracy through factors, namely Subjective Norms (SN), Perceived Behavior Controls (PBC), and Attitude (ATD), along with variations in Behavior emerging from different notions of behavior control. Ajzen (2011) clarified that other contextual elements can broaden our understanding of humans' social interactions, attitudes, and actions. The TPB provides a framework for the direction of human action or forecasts —if intentional— its occurrence through observing the relationship between the factors and Behavior. It is important to mention that the TPB was not widely utilized or proven to successfully measure the relation between the Intention and the actual individuals' behavior or action. However, according to Ajzen (2020), Intention can be utilized as a proximal measure of conduct even when the relation between behavioral intention and actual behavior is not perfect, which could be considered one of the drawbacks of the theory (Ajzen, 2020).

Figure 1
Theory of Planned Behavior (TPB)



Note. From The Theory of Planned Behavior. By Ajzen, 1991, Organizational Behavior and Human Decision Processes

Attitude

Attitude is a favorable or unfavorable assessment of the Behavior. It is believed that attitude is determined by a person's salient ideas of a conduct's negative and positive effects. Therefore, when an individual believes that a behavior's benefits outweigh the downsides, they are believed to have a positive attitude (Ajzen & Fishbein, 2000).

Subjective Norms

Subjective norms come from normative beliefs of whether perceived societal pressure to engage or disengage in Behavior will affect behavioral Intention. Subjective norms are commonly pronounced by those important/close to the individual. Normative beliefs affecting subjective norms are divided into injunctive and descriptive beliefs. Injunctive beliefs are the likelihood that a reference group of individuals will make their opinion on the Behavior known. Alternately, Descriptive beliefs are views on whether they practice the Behavior or not (Ajzen, 1991; Ajzen, 2002; Ajzen, 2011; Ajzen & Fishbein, 2000; Ajzen & Fishbein, 2005).

Perceived Behavior Controls

Perceived behavioral controls are shaped by control beliefs that appear through information hindering or encouraging individuals to partake in Behavior during situations of interest. Elements such as time, financial capability, experience, and other resources are all control factors (Ajzen, 1991; Ajzen, 2002; Ajzen & Fishbein, 2005).
The theory does acknowledge that there may be other different background circumstances that can influence how beliefs are formed and impact intention and Behavior itself. Background characteristics such as social structure, demographics, and personal traits have been highlighted as responsible for behavioral variations Ajzen (2011). The Normative, Behavioral, and Control beliefs contain the most in-depth substantial knowledge about the influencing factors (Ajzen, 2020).

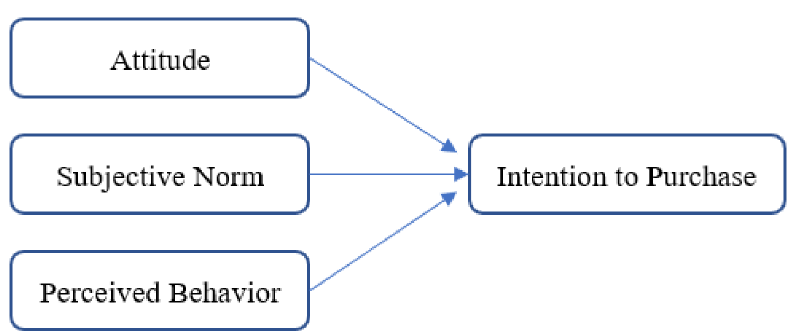
Theoretical Framework

The TPB is a general theory and is not specific on studying the purchasing intention of RE properties. However, the decision to utilize its theoretical framework in this study is supported by the existence of other recent studies that have used it for the same purpose in the real estate field (Al-Nahdi, A.Habib & A.Albdour, 2015; Al-Nahdi, Emmanuel, et al., 2015; Judge et al., 2019; Lei, 2016; Tan, 2013). In these studies, the TPB was utilized for testing the significance of its factors —ATDs, SNs, and PBCs— on the Intention of purchasing residential in KSA, Thailand, Malaysia, and Australia. In most cases, it was concluded that the TPB independent factors are significant predictors of the RE purchasing intention. Accordingly, the TPB theoretical framework has proven to explain the RE purchasing Intention. It is worth mentioning that few of those researchers have developed upon the factors of the TPB in their own studies; the researcher did not do so as these are individual cases (Lei, 2016; Tan, 2013).

To carry out this quantitative study, the researcher employed the TPB factors to examine them empirically. The dependent variable is the Intention to purchase RE properties, while the independent variables are ATDs, SNs, and PBCs.

Figure 2

The Theoretical Framework Proposed by the Author



Research Hypothesis

The research hypotheses were derived from the proposed theoretical framework for each independent factor to investigate its relation to the dependent factor.

The first Null hypothesis (H1a) states that attitude will have no influence on expatriates' Intention to purchase RE properties in Dubai. In contrast, the Alternative hypothesis (H1b) states that the more positive the attitude, the greater the expatriates' Intention to purchase RE in Dubai.

The second Null hypothesis (H2a) states that Subjective norms will have no influence on expatriates' Intention to purchase RE properties in Dubai. In contrast, the Alternative hypothesis (H2b) states that the more positive the Subjective Norms, the greater the expatriates' Intention to purchase RE in Dubai.

The Null hypothesis (H3a) states that Perceived Behavior Controls will have no influence on the expatriates' Intention to purchase RE properties in Dubai. In contrast, the Alternative hypothesis (H3b) states that the more positive the Perceived Behavior Controls, the greater the expatriates' Intention to purchase RE in Dubai.

Methods and Materials

The primary data collection instrument of this quantitative study was adopted from the study developed by Al-Nahdi, Habib & A.Albdour (2015). The determined sample was 384 persons who underwent inclusion criteria ensuring the sample represents the targeted population. The survey questionnaire encompasses two main sections: (1) The demographic data of participants, which was designed as a multiple-choice format that inquiries into marital status, income, education, age, citizenship, gender, and type of employment, and (2) “The participants’ views of purchasing property in Dubai” section which is divided into four sub-sections representing the dependent and independent factors that constitute Ajzen's TPB through a 5-point Likert scale (Refer to Appendix B).

Research Population

This targeted population comprises households and individuals following the specified inclusion criteria. First, being expatriates or non-Emiratis who reside and/or work in Dubai or the adjacent emirates. Second, they should match the eligible age for property purchasing but below the retirement age, within the 18-60 years old bracket. Third, Being current employees, business owners, self-employed, or individuals with other sources of income. Finally, being financially capable of purchasing a property or paying a home loan monthly installment. The financial capability threshold was identified by following the UAE banks’ required minimum monthly income of AED 10,000 —USD 2,725— for accepting home loan requests from individuals, a minimum of AED 15,000 to afford household expenditures, and housing bank installments for 2-member families, a minimum of AED 18,000 for 3-member families, a minimum of AED 20,000 for 4-member families, and minimum monthly income of AED 25,000 for five-member families. The target population size of this study is 405,000 households —the same number of residential unit rentals in Dubai in 2020 (Dubai Land Department, 2020; Dubai Statistics Center, 2014; Dubai Statistics Center, 2015; Dubai Statistics Center, 2021a; “Home in one”, 2022).

Sample Size

Sampling was done utilizing a random sampling technique, and since the target population exceeds the 100,000 mark, 384 participants were required in compliance with the Saunders et al. (2009) table of sample size identification at a 95% confidence level.

Data Collection and Processing

The instrument was a digitally self-administered close-ended survey questionnaire randomly distributed to participants online via emails, digital platforms, and smartphone applications such as LinkedIn, WhatsApp, Instagram, and Facebook. Due to time constraints, this research was conducted at a single moment in time, making it cross-sectional. The completion of collecting all the responses of participants took place in February 2023.

Results

Response rate

Out of the 609 total responses, only 384 or 63% sets were useable. The analysis of the distributed questionnaires is shown in Table 1. Abiding by the inclusion criteria, 37% of the responses received from the participants were eliminated.

Table 1
Questionnaire Responses Analysis

Items	Number	Percentage
Unusable responses	225	36.95%
Did not consent to participate	6	0.99%
Not matching the inclusion criteria	219	35.96%
Usable responses	384	63.05%
Total responses	609	100%

Profile of Respondents

To observe the socio-demographic characteristics of the survey respondents, the researcher conducted a descriptive analysis of their profiles. The analysis revealed that responses of the participants aged 18 to 30 years old represented 5.99% of the total responses, between 31 to 40 represented 48.18%, and between 41 to 59 represented 45.83%. The gender ratio split was 79.17% males to 20.83% females. 81.25% of the respondents were married, 17.71% were single, and 1% marked other marital statuses. 15.1% live alone in the UAE, 11.98% have a two-member family, 20.83% have a 3-member family, 35.64% have a 4-member family, and 17.45% have a 5-member family or above. None of the respondents marked primary or secondary level education as the highest, whereas 1.56% marked Diploma level, 62.24% held bachelor’s degrees, 30.21% held postgraduate degrees, and 5.99% were professional qualification holders. Furthermore, 4.95% own a private business, 7.29% work in government entities, and 87.76% work in the private sector.

Table 2
Profile of Respondents

Respondent’s profile	Category	Frequency	Percentage
Age	18 to 30	23	5.99%
	31 to 40	185	48.18%
	41 to 59	176	45.83%
Gender	Male	304	79.17%
	Female	80	20.83%
Marital Status	Single	68	17.71%
	Married	312	81.25%
	Other	4	1.04%
Number of family members	1	58	15.10%
	2	46	11.98%
	3	80	20.83%
	4	133	35.64%
	5 or above	67	17.45%
Education	Primary level	0	0
	Secondary level	0	0
	Diploma	6	1.56%
	Bachelor’s degree	239	62.24%
	Postgraduate	116	30.21%
	Professional qualification	23	5.99%
Occupation / Employment	Self-employed	19	4.95%
	Government Employed	28	7.29%
	Private Sector Employed	337	87.76%

Data Analysis

To examine the datasets and test the proposed hypothesis, the researcher utilized the statistical software SPSS version 17.0. The following subsections represent the sequence in which the analytical testing was performed (IBM, 2021).

Absence of Outliers Among Cases

The data set was tested to indicate univariate outliers in the independent and dependent items. Outliers are values not in the +3.29 to -3.29 standard deviation range. No outliers were detected in all the datasets collected from the usable 384 participants (Tabachnick & Fidell, 2013).

Factor Analysis

The Factor Analysis (FA) test was performed on all items measuring independent variables to confirm whether the items for variables are simplified or not. The test establishes a link between the factors and their related variables, where the variables are grouped under the number of factors initially hypothesized (Shrestha, 2021).

The following methods are used in the FA testing. First, the Principal Components method is concerned with the sequence of variances extraction and assigning them to the hypothesized number of factors. Second, the Varimax Rotation method analyzes factors' structure and correlations between items included on the scale. It is an orthogonal rotation technique, meaning that interpretation of the factors is much easier through its reduction of the number of variables that each factor is assigned (IBM, 2021). Third, the Kaiser-Meyer-Olkin metric of sampling adequacy (KMO) was used to test the sample adequacy of each variable. The higher the variable, the better the data suitability for FA. Values are on a scale of 0.0 to 1.0, where the minimum acceptable value is 0.60; a value of 0.8 or bigger is found to be adequate (Shrestha, 2021; Tabachnick & Fidell, 2013). Fourth, Bartlett's test of sphericity is necessary to determine whether the factors are orthogonally perfect or not. If the correlation matrix of the variables deviates from the identity matrix, the factor analysis will be unacceptable (IBM, 2021). The Bartletts test of sphericity p-value should be significant <0.05. Fifth, the Eigenvalue that demonstrates a factor's capability to explain the total variance should not be less than 1.0 for all the components (Shrestha, 2021).

Table 3

Factor Loading for Independent Variable - Rotated Component Matrix

	Component		
	1	2	3
Factor: Attitude			
Buying a residential property in Dubai is a beneficial decision	.274	**.862**	.137
Buying a residential property in Dubai is a good idea	.298	**.870**	.110
Buying a residential property in Dubai is a wise decision	.323	**.874**	.090
Buying a residential property in Dubai is an admired decision	.346	**.789**	.119
Factor: Subjective Norm			
My family thinks that I should buy a property in Dubai	**.897**	.307	.123
My family would want me to buy a property in Dubai	**.898**	.313	.158
My family agrees with me to buy a property in Dubai	**.875**	.349	.139
My family thinks that buying a property in Dubai is a wise decision	**.887**	.316	.119
Factor: Perceived Behavior			
I have enough opportunity in making a decision to buy a property in Dubai, and I have easy access to the market.	.164	.170	**.781**
I have enough time to make a decision to buy a property in Dubai	.110	.163	**.792**
I have enough money to pay the advanced payment to buy a property in Dubai	.052	.017	**.794**
I have enough skills and knowledge about real estate to make my own decision If I would like to buy a property in Dubai.	.068	.142	**.771**
I have complete control over buying a property in Dubai	.090	-.026	**.727**
Eignevalue	6.318	2.54	1.240
Total variance explained		77.677%	
Kaiser-Meyer-Olkin MSA (KMO)		0.899	
Bartlett's test of sphericity – Approx. Chi-square		4328	
– df		78	
– Sig.		0.00	

The findings of FA confirmed that the model is based on the three initially hypothesized independent factors, and all items tested are loading on their proposed factors. Moreover, the findings revealed that the total variance explanation for the three independent factors is at 77.677%, the KMO measure of sampling adequacy is at a value of 0.899 (adequate), the Bartletts test of sphericity is at a 0.0 p-value (significant), and that the Eigenvalue values are higher than 1.0 for the three factors (significant).

Table 4
Factor Loading for the Dependent Variable - Component Matrix

Factor: Intention	**Components**
I will continue to buy a property in Dubai in the future	0.899
I intend to buy a property in Dubai frequently in the future	0.918
I plan to buy a property in Dubai	0.930
I will try to buy a property in Dubai	0.866
I want to buy property in Dubai	0.782
Eignevalue	3.878
Variance %	77.551%
Kaiser-Meyer-Olkin MSA (KMO)	0.882
Bartlett's test of sphericity – Approx. Chi-square	1589
df	10
Sig.	0.00

The FA test on the dependent variables was carried out by proposing five questions to represent the dependent variable. The factor total variance explanation is 77.55%, the KMO measure of sampling adequacy was at 0.882 (adequate), the Bartletts test of sphericity shows a 0.0 p-value (significant), and the Eigenvalue is 3.87 (significant).

Reliability Analysis

The Reliability analysis test aims at understanding and studying the items comprising this study's measurement scale. The Cronbach alpha test- consisting of a 0 to 1 value range- was conducted to gauge the instrument's degree of reliability. A 1.0 score indicates 100% reliability, while a 0.70 is the minimum acceptable value (Brown, 1997; Shrestha, 2021).

Table 5 demonstrates Cronbach's alpha values for the dependent and independent variables, indicating acceptable values above 0.70 for all items (Brown, 1997).

Table 5
Reliability Testing of Independent Variables

Variables	**No. of items**	**No. of items retained**	**Cronbach Alpha**
Attitude	4	4	0.931
Subjective Norms	4	4	0.968
Perceived Behavior	5	5	0.843
Intention	5	5	0.927

Descriptive Analysis

The results of the independent variables — ATDs, SNs, PBCs — and the dependent variable — Intention — descriptive analysis results are listed in Table 6.

Table 6
Descriptive Analysis

Variable	Mean	Std. Deviation
Attitude	3.632	0.948
Subjective Norms	3.339	1.20
Perceived Behavior control	3.328	0.875
Intention	3.379	1.057

Multiple regression assumptions

Testing the multiple regression assumptions is done to ensure the dataset quality. These assumptions often underlie multiple regression, including six tests. Three of these conditions are targeted at the error terms of the regression equation; error terms are assumed to be homoscedastic, independent, and normally distributed. The other assumptions concentrate on the relations' functional form between independent and dependent variables: linearity, the absence of multicollinearity, and the absence of influential observations (Best & Wolf, 2015).

There exists a graphical method for analyzing linearity and normality. Linearity is imperative for using regression analysis as a descriptive analysis (Best & Wolf, 2015), where the dependent and independent relation elements are presumed linear. Usually, the regression model assumes that the distribution of residuals or error terms has a specific form. On the other hand, normality requires that the error terms settle into a normal distribution.

Figures 3, 4, and 5 visually illustrate that no linearity-related issues are present, whereas the standardized residuals are normally distributed.

Figure 3
Normal P-P Plot

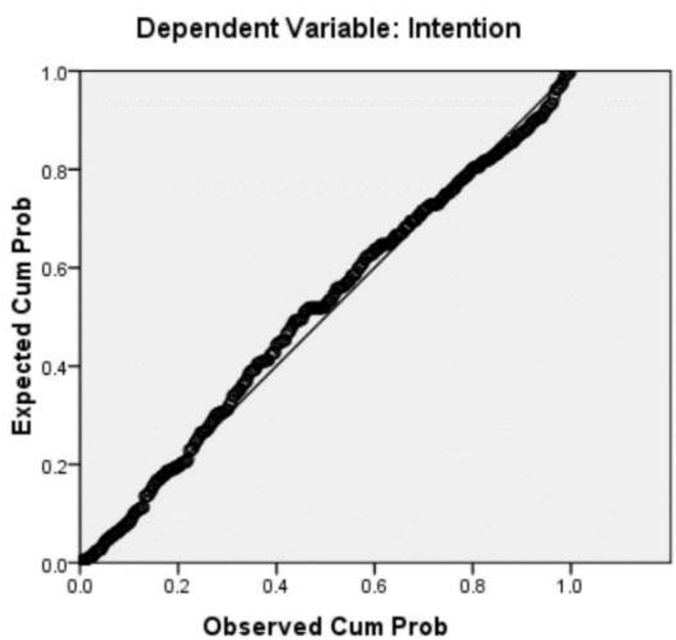


Figure 4
Scatterplot

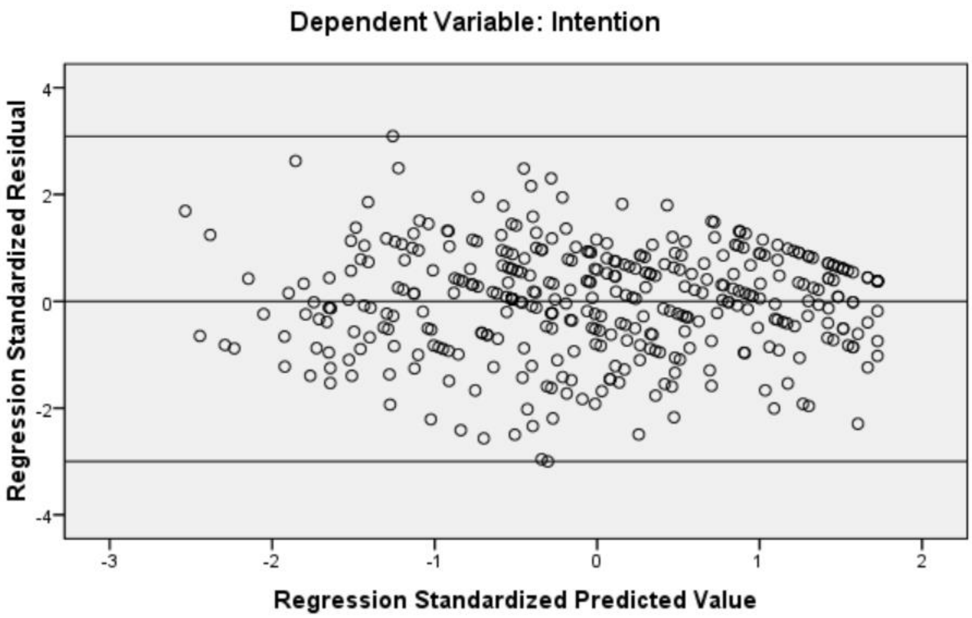


Figure 5
Histogram

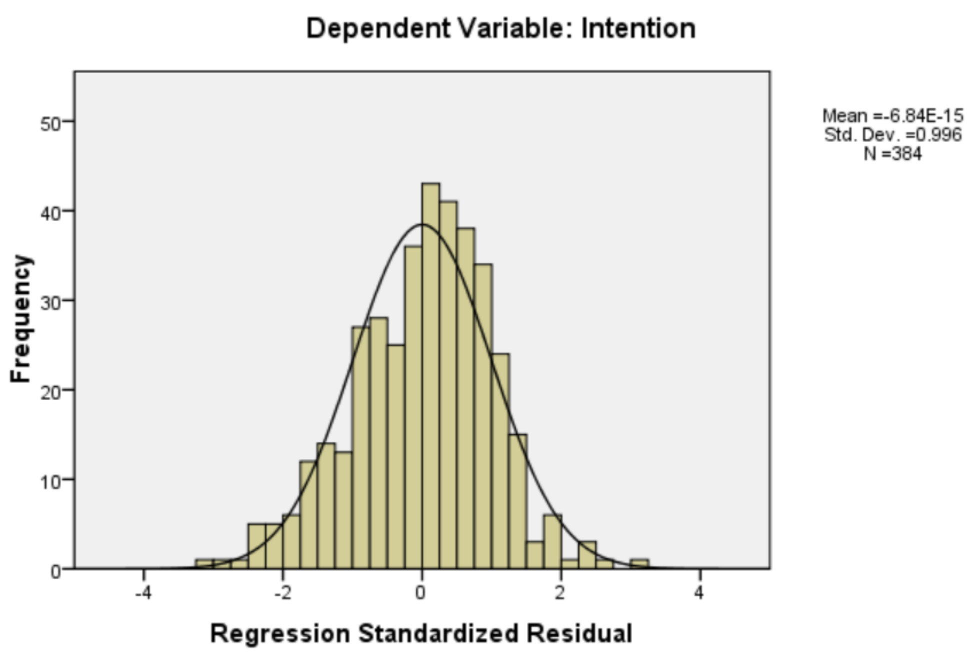


Figure 5 presents the typical bell shape with a P-P plot and a scattered plot. The standardized residuals are compared with the normal distribution. When examining the P-P plot, the data lies in a straight line, indicating no linearity and normality-related issues. In the scattered plot, the data is centralized, equally distributed in the chart, and falls between -3 and +3 (Fein et al., 2022).

The Homoscedasticity presumption relates to the dispersion of the model's error components or residuals. Alternatively, Heteroscedasticity describes a situation in which the variance of the residuals is not constant (Best & Wolf, 2015). If Heteroskedasticity is present, that highlights a violation in the assumptions of the linear regressions model; Heteroskedasticity must not be present in the residuals (White, 1980). The Breusch-Pagan test is used to examine whether the variance of the dependent variable's errors has any dependency on the value of the independent variables (IBM, 2021). Using the SPSS, the test results exhibit a significant value of 1.0 (> 0.05), concluding that there is no Heteroskedasticity in the data (Zeileis & Hothorn, 2002).

To test the independence of residuals - in cases matching the selection condition- the Durbin-Watson test examines the serial correlation of the residuals and case-specific diagnostic data (Best & Wolf, 2015; IBM, 2021). The test result was found to be 1.873, close to the ideal value of 2.0, relaying that there is no significant autocorrelation in the data (Best & Wolf, 2015; Mourougan & Sethuraman, 2017).

A situation of collinearity between the independent variables of a model or the redundancy in the set of variables is referred to as multicollinearity (Sykes, 1993). When testing collinearity diagnostics (where none of the independent variables have a high correlation between them), it was found that collinearity rests at 0.8. Simultaneously, the condition index accumulative value was 12.91 (<30.00). When the results of the collinearity statistics in coefficient analysis were interpreted, the tolerance of all variables was below 1.0, and the collinearity variance influencing factors (VIF) was below 10. This concluded that the model has no collinearity and no overlap amongst the independent variables (Farrar & Glauber, 1964).

To check the individual sample cases' influence on fitted models (Best & Wolf, 2015), the researcher utilized Cook's distance value, in which the residual statistics distance analysis shows a maximum value of 0.044. 0.044, being less than 1.0, implies no outliers exist in the predictor variables data (Boussiala, 2020; Asemota & Asemota, 2022). Moreover, the value for all the dataset's standardized residuals lies between -3 and +3 (Fein et al., 2022).

Test for Hypothesis

While the multiple regression technique is focused on determining the relation between the independent and dependent variables, the regression analysis technique is focused on testing the proposed hypotheses.

The proposed hypotheses stated that the relation between the independent factors (ATDs, SNs, and PBCs) and the dependent factor (Intention) is one of positive correlation. To ascertain this relation, the researcher utilized the regression analysis technique. To produce — through the multiple regression technique— a straight line through the data set (to be significant), the relationship between the independent and dependent variables must be linear. Furthermore, the independent variables themselves must not be significantly linked amongst themselves (“Regression analysis,” 2023).

The findings demonstrated in Table 7 show that R2 = 54.9%. Therefore, the findings exhibit that the independent variables taken together can account for 54.9% of dependent variable variation. Moreover, the model was found to be acceptable, as the F value was that of 153.9 and the p-value was that of 0.00 (R2 = 0.549, F(3, 380) = 153.9, p = 0.00). The overall regression is statistically significant. The fitted regression equation is: Predicted Intention = 0.388 (ATDs) + 0.376 (SNs) + 0.118 (PBCs) + 0.322 (constant), per one unit increase in each factor.

Table 7
Multiple Regression Analysis Results

Variable	Unstandardized Coefficient (B)	Standardized Coefficient Beta	P-Value
Constant	0.322		
Attitude	0.388	0.348	0.00
Subjective Norms	0.376	0.427	0.00
Perceived Behavior	0.118	0.098	0.007
R^2	0.549		
Adjusted R^2	0.545		
F	153.9		
Sig.	0.00		
Durbin-Watson Test	1.902		

When testing ATD's magnitude toward the purchasing intention of RE, ATD is found to be significant at 0.00 ($p \leq 0.05$), Standardized Coefficients Beta was at (β) =0.348, and a positive impact on the RE purchasing Intention existed (β = 0.348, p = 0.0). When analyzing the Standard Coefficient Beta analysis result, it was apparent that one increase of standard deviation in ATD resulted in a 0.348 Standard deviation unit increase in Intention. Then, the alternative hypothesis was accepted.

When testing SN's magnitude towards the purchasing intention of RE, SN is found to be significant at 0.00 ($p \leq 0.05$), (β) at 0.348, and a positive impact on the RE purchasing Intention existed (β = 0.427, p = 0.00). When analyzing the Standard Coefficient Beta analysis result, it was apparent that one increase of standard deviation in Subjective norms results in a 0.427 Standard deviation unit increase in Intention. Then, the alternative hypothesis was accepted.

When testing PBC's magnitude toward the purchasing intention of RE, PBC is found to be significant at 0.007 ($p \leq 0.05$), β = 0.098, and a positive impact on the RE purchasing Intention existed (β = 0.098, p = 0.007). When analyzing the Standard Coefficient Beta analysis result, it was apparent that one standard deviation increase in Perceived Behavior Controls resulted in a 0.098 Standard deviation unit increase in Intention. Then, the alternative hypothesis was accepted.

Table 8
Hypotheses Testing Results Summary

Hypothesis	Accept / Reject
H1b the more positive the attitude, the greater the expatriates’ intention to purchase real estate in Dubai	Accept
H2b the more positive the subjective norms, the greater the expatriates’ intention to purchase real estate in Dubai	Accept
H3b The more positive the perceived behavioral control, the greater the expatriates’ intention to purchase real estate in Dubai	Accept

Implications

It is of the findings' potential to aid researchers, policymakers, RE professionals, and developers in gaining valuable information. It can help the government, legislators, and RE regulators in their objectives to formulate and refine the laws and regulations that promote property purchasing by the expatriates, also the same findings could assist the RE developers, marketing, and sales professionals to understand the factors influencing expatriates' purchasing intention —ATD, SNs, and PBCs, and accordingly allow to generate better sales and marketing strategies to positively influence their purchasing intention.

Also, the respondents' profile analysis is beneficial in better targeting potential buyers based on their socio-demographic characteristics. Considering the assumption that the suitably sized sample population is representative of the full population of buyers according to Saunders_et al. (2009), the sample analysis of this study is expected to represent the whole population of potential RE buyers in Dubai, and the outcome of the analysis of respondents' socio-demographic profiles after applying the inclusion criteria could significantly help RE professionals to identify and detect potential property buyers, as 94% of the participants were between the ages of 31 and 59, also, the approximate gender split of the sample is 20% females to 80% males, while the 3-member and 4-member family size is 56% of all categories when combined. Education level was significantly concentrated at bachelor's degree and higher educational levels, exceeding 98% of the included participants. The private sector-employed participants represented more than 87% of the sample members.

Comparisons

Comparing the results of the study conducted by other several researchers in several countries utilizing the TPB with the results of this research, it was found the three independent factors in most of these studies influence purchasing intention. Refer to Table 9.

Table 9

Summary of the Most Relevant Studies to the Scope of this Research

Reference	Location	Dependent factor	Independent factors	Hypotheses test results
Al-Nahdi, A.Habib & A.Albdour (2015)	Jeddah, KSA	Property purchasing Intention	ATD SNs PBCs	ATD – Accepted SNs – Accepted PBCs – Not Accepted
Tan (2013)	Malaysia	Green and sustainable property purchasing Intention	ATD SNs PBCs	ATD – Accepted SNs – Accepted PBCs - Accepted
Lei (2016)	Bangkok, Thailand	Property purchasing decision	ATD SNs PBCs	ATD – Accepted SNs – Accepted PBCs - Accepted
Judge et al. (2019)	Australia	Sustainable property purchasing Intention	ATD SNs PBCs	ATD – Accepted SNs – Accepted PBCs - Accepted
This research - 2023	Dubai, UAE	Property purchasing Intention	ATD SNs PBCs	ATD – Accepted SNs – Accepted PBCs - Accepted

Conclusion

This research study has demonstrated the ability of the TPB to explain the purchase intention of properties by expatriates in Dubai. It was concluded that the intention to purchase residential properties in Dubai was influenced by ATD, SNs, and PBCs, with the SNs and the ATD elements being more influential, respectively. The three independent factors—ATD, SNs, and PBCs—in combination explained 54.9% of the variance in the intention of purchasing RE properties in Dubai. On the other hand, the result of the respondents' profile analysis showed concentration in many of the potential buyers' socio-demographic brackets.

Limitations and Delimitations

Although additional factors may pose as moderating or mediating factors on the dependent factor of this study, the researcher decided to descope the identification of other potential factors. This is due to the lack of existing studies that established additional factors in successfully tested theoretical frameworks. Therefore, the researcher opted for this exclusion due to the time constraints. The research could not study the relationship between the independent factors and the actual Behavior, as these might be influenced by various contextual restrictions that cannot be identified; similarly, according to Ajzen (2011), the TPB model was criticized for its incapability of accurately acknowledging the PBCs and INT contributions to Behavior.

On the contrary, the researcher chose to study Dubai's real estate only, not including the geographically nearby Emirates, to render it more manageable considering the limited timeframe and the researcher's capacity. Furthermore, the researcher chose to focus on Dubai's expatriates as the main population for this research and excluding other categories of buyers such as the local Emiratis and international investors, the researcher found this main population suitable due to its high categorical volume compared to the rest of the categories.

Recommendations for Future Studies

This study has the potential to source more protracted studies. The researcher suggests several ideas for unfurling and maximizing opportunities for utilizing this study in future research, specifically in three areas:

First, the introduction of additional factors to the research model to increase the percentage of the variance found in the dependent variable since ATD, SN, and PBC only explained 54.9% of the variance in the dependent factor —INT, alluding to more room for additional factors. In this context, the researcher suggests three other potential factors to be tested: finance, financial literacy, and job insecurity.

Second, this study can be used as a starting point and a reference for coming studies in similar scopes, such as other real estate buyer categories or the expatriates residing in other Emirates or the nearby Arabian Gulf states' RE markets.

Finally, developing a framework that aims to forecast the demand for RE purchasing, which combines the identified factors, the concluded potential buyers' demographic data in this research, the traditional factors utilized in the traditional methods of RE demand forecasting, historical data, market trends, and seasonal cycles, based on which, from a practical standpoint, the framework could be applied to develop AI-based customers' outreach tools, which can be used to influence expatriates' Intention and also to forecast demand based on potential buyer's planned Behavior.

References

Abbas, W. (2018, May 21a). *Why construction industry is booming in Dubai.* Khaleej Times. https://www.khaleejtimes.com/business/why-construction-industry-is-booming-in-dubai

Abbas, W. (2018, March 15b). *Expats in Dubai earn more than most of the global cities.* Khaleej Times. https://www.khaleejtimes.com/business/expats-in-dubai-earn-more-than-most-of-the-global-cities

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211. https://www.researchgate.net/publication/272790646_The_Theory_of_Planned_Behavior

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology*, *32*(4), 665–683. https://onlinelibrary.wiley.com/doi/10.1111/j.1559-1816.2002.tb00236.x

Ajzen, I. (2011). The theory of planned behaviour: Reactions and reflections. *Psychology and Health*, *26*(9), 1113–1127. https://doi.org/10.1080/08870446.2011.613995

Ajzen, I. (2020). The theory of planned behavior : Frequently asked questions. *Human Behavior and Emerging Technology*, *2*(4), 1–11. https://www.tandfonline.com/doi/full/10.1080/08870446.2011.613995

Ajzen, I., & Fishbein, M. (2000). Attitudes and the Attitude-Behavior Relation: Reasoned and Automatic Processes. *European Review of Social Psychology*, *11*(1), 1–33. https://doi.org/10.1080/14792779943000116

Ajzen, I., & Fishbein, M. (2005). The influence of attitudes on behavior. In D. Albarracín, B. T.

Johnson & M. P. Zanna (Eds.), *The Handbook of Attitudes* (pp. 187–236). Lawrence Erlbaum Associates. https://www.researchgate.net/publication/264000974

Al-Nahdi, T., A.Habib, S., & A.Albdour, A. (2015). Factors influencing the Intention to purchase real estate in Saudi Arabia: Moderating effect of demographic citizenship. *International Journal of Business and Management*, *10*(4), 35–48. https://doi.org/10.5539/ijbm.v10n4p35

Al-Nahdi, T., Emmanuel, N., M.Banamah, A., & A.Jappie, A. (2015). Factors affecting purchasing behavior in real estate in Saudi Arabia. *International Journal of Business and Social Science,* *6*(2), 113–125. http://www.ijbssnet.com/journals/Vol_6_No_2_February_2015/16.pdf

Ali, S. (2011). Going and coming and going again: Second-generation migrants in Dubai. *Mobilities*, *6*(4), 553–568. https://doi.org/10.1080/17450101.2011.603947

Asemota, O. O., & Asemota, G. N. O. (2022). Influence of adherence to academic employee work contract on academic employee commitment in selected Kenya public universities. *Journal of Popular Education in Africa*, 6(10), 53–77. https://shorturl.at/jGSZ7

Bell, J. (2021, October 14). *Majority of UAE expats failing to save for retirement, financial experts warn.* Alarabiya. https://english.alarabiya.net/News/gulf/2021/10/14/Majority-of-UAE-expats-failing-to-save-for-retirement-financial-experts-warn

Best, H., & Wolf, C. (Eds.). (2015). *The SAGE handbook of regression analysis and causal inference*. Sage Publications. http://ndl.ethernet.edu.et/bitstream/123456789/26799/1/122.Henning%20Best%2C%20Christof%20Wolf-.pdf

Boonroungrut, C., & Huang, F. (2020). Reforming theory of planned behavior to measure money management intention: a validation study among student debtors. *RAUSP Management Journal,* *56*(1), 24–37. https://rb.gy/1b9ryr

Boussiala, M. (2020). *Cook's distance*. University of Southern Queensland. https://usq.pressbooks.pub/statisticsforresearchstudents/

Bridge, S. (2018, October 11). *Revealed : how much the average expat earns in the UAE*. Arabian Business.

Bridge, S. (2019, May 2). *Millennials lead rush to buy The Nook homes in Dubai.* Arab Business. https://www.arabianbusiness.com/interviews/property/property-news/419302-millennials-lead-rush-to-buy-the-nook-homes-in-dubai

Brown, J. D. (1997). *Reliability of surveys.* JALT Testing & Evaluation SIG. https://hosted.jalt.org/test/PDF/Brown2.pdf

Carvalho, S. (2005). *Remittances put burden on economy.* Gulf News. https://gulfnews.com/business/banking/remittances-put-burden-on-economy-1.281311

Cave, B. (2004). *Legal issues related to doing business in the United Arab Emirates.* Bryan Cave LLP. https://www.bclplaw.com/images/content/8/1/v2/814/MiddleEastArticle2-04.pdf

Central Bank (2020). *Annual report 2020*. https://www.centralbank.ae/media/dqekezdp/cbuae-annual-report-2020.pdf

Dubai Land Department (2020). *Annual Report.* https://dubailand.gov.ae/media/4uigpvwf/annual-report-real-estate-sector-performance-2020.pdf

Dubai Land Department (2022). *Annual report: Dubai real estate Sector Performance 2021.* https://dubailand.gov.ae/en/open-data/research/annual-report-real-estate-sector-performance-2021/#/

Dubai Land Department (2023). *Residential sales price index*. Dubai Land Department. Dubai Land Department - Indexes

Dubai Statistics Center (2014). Annual Average of Household Expenditure and Consumption by Expenditure Divisions - Emirate of Dubai. https://www.dsc.gov.ae/Report/T 01.pdf

Dubai Statistics Center (2015). Relative distribution of annual households consumption by expenditure divisions. https://www.dsc.gov.ae/Report/T 05.pdf

Dubai Statistics Center (2020). *Housing units (Urban and Rural) by Type - Emirate of Dubai.* https://www.Dubai Statistics Center.gov.ae/Report/DUBAI STATISTICS CENTER SYB 2020 02 02.pdf

Dubai Statistics Center (2021a). *Consumer price index 2021.* https://www.Dubai Statistics

Center.gov.ae/Report/Consumer Price Index 2021.pdf

Dubai Statistics Center (2021b). *Employees by economic activity - Emirate of Dubai.* https://www.Dubai Statistics Center.gov.ae/Report/العمالة حسب النشاط الاقتصادي- لإمارة دبي 2020.pdf

Dubai Statistics Center (2021c). *Gross domestic product at current prices for 2020.* https://www.Dubai Statistics Center.gov.ae/Report/Gross Domestic Product at Current Prices 2020 - Emirate of Dubai 2020 .pdf

Dubai Statistics Center (2021d). *Population bulletin.* https://www.Dubai Statistics Center.gov.ae/Publication/Population Bulletin Emirate of Dubai - 2020.pdf

Dubai Statistics Center (2022). *Population and Vital Statistics.* Data Statistics Center. https://www.dsc.gov.ae/en-us/Themes/Pages/Population-and-Vital-Statistics.aspx?Theme=42&year=2022#DSC_Tab1

Dubai real estate growing fastest in the world (2022, November 29). Arabian Business. https://www.arabianbusiness.com/industries/real-estate/dubai-real-estate-growing-fastest-in-the-world-report

Farrar, D. E., & Glauber, R. R. (1967). Multicollinearity in regression analysis: The problem revisited. *The Review of Economics and Statistics, 49*(1), 92–107. https://doi.org/10.2307/1937887

Fein, E. C., Gilmour, J., Machin, T., & Hendry, L. (2022). *Statistics for research students.* University of Southern Queensland. https://usq.pressbooks.pub/statisticsforresearchstudents/

Forstenlechner, I., & Rutledge, E. J. (2011). The GCC's "demographic imbalance": Perceptions, realities and policy options. *Middle East Policy, 18*(4), 25–43. https://www.academia.edu/1083542/The_GCC_s_Demographic_Imbalance_Perceptions_Realities_and_Policy_Options?from=cover_page

Getting on the property ladder: Millennial home buyers in the UAE (2020). My Bayut. https://www.bayut.com/mybayut/millennial-home-buyers-investing-dubai-real-estate/

Gopi, M., & Ramayah, T. (2007). Applicability of theory of planned behavior in predicting intention to trade online: Some evidence from a developing country. *International Journal of Emerging Markets, 2*(4), 348–360. https://www.academia.edu/10278460/Applicability_of_theory_of_planned_behavior_in_predicting_intention_to_trade_online_Some_evidence_from_a_developing_country

Hrubes, D., Ajzen, I., & Daigle, J. (2001). Predicting hunting intentions and behavior: An application of the theory of planned behavior. *Leisure Sciences, 23*(3), 165–178. https://www.researchgate.net/publication/255636069_Predicting_Hunting_Intentions_and_Behavior_An_Application_of_the_Theory_of_Planned_Behavior

Home in one: Go for a mortgage loan that saves you interest (2022). RAK Bank. https://rakbank.ae/wps/portal/retail-banking/loans/personal/home-in-one

IBM. (2021). *IBM SPSS statistics base 28.* https://www.ibm.com/docs/en/SSLVMB_28.0.0/pdf/IBM_SPSS_Statistics_Base.pdf

Knabe, A. (2012). Applying Ajzen's theory of planned behavior to a study of online course adoption in public relations education (Publication No. 1934-186) [Doctorate Dissertation, Marquette University] e-Publications@Marquette. https://epublications.marquette.edu/cgi/viewcontent.cgi?article=1186&context=dissertations_mu

Kumar, A. (2018, October 24). 91% Expats in UAE workforce: Experts call for Emiratisation. *Khaleej Times*. https://www.khaleejtimes.com/uae/91-expats-in-uae-workforce-experts-call-for-emiratisation

Lejeune, C., Pagès-El Karoui, D., Schmoll, C., & Thiollet, H. (2021). *Migration, urbanity and cosmopolitanism in a globalized world.* Springer. https://doi.org/10.1007/978-3-030-67365-9_1

Montaño, D. E., & Kasprzyk, D. (2015). Theory of reasoned action, theory of planned behavior, and the integrated behavioral model. In K. Glanz, B. K. Rimer, & K. V. Viswanath (Eds.), *Health behavior: Theory, research, and practice* (pp. 95–124). Jossey-Bass/Wiley. https://www.researchgate.net/publication/233894824

More than 2,000 Emiratis join private sector after government drive. (2021, December 15). The National News. https://www.thenationalnews.com/uae/2021/12/14/more-than-2000-

emiratis-join-private-sector-after-government-drive/
Mourougan, S., & Sethuraman, D. K. (2017). Hypothesis development and testing. *IOSR Journal of Business and Management, 19*(05), 34–40. https://doi.org/10.9790/487x-1905013440
Nair, D. (2018, August). Millennials warm up to buying property in Dubai. *Khaleej Times*. https://www.khaleejtimes.com/business/real-estate/millennials-warm-up-to-buying-realty-in-dubai
Regression analysis: The ultimate guide (2023). Qualtrics.https://www.qualtrics.com/experience-management/research/regression-analysis/
Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for business students.* Pearson.
Sawy, N. El. (2020, February 25). Almost half of UAE expatriates have no financial plan to fund their retirement. *The National News*. https://www.thenationalnews.com/business/money/almost-half-of-uae-expatriates-have-no-financial-plan-to-fund-their-retirement-1.984081
Shrestha, N. (2021). Factor analysis as a tool for survey analysis. *American Journal of Applied Mathematics and Statistics, 9*(1), 4–11. article.sciappliedmathematics.com/pdf/ajams-9-1-2.pdf
Swan, M. (2017, December 22). Is your lonely UAE life making you sick? Gulf News. https://gulfnews.com/friday/wellbeing/is-your-lonely-uae-life-making-you-sick-1.2141147
Sykes, A. O. (1993). *An introduction to regression analysis.* (Coase-Sandor Institute for Law and Economics Working Paper No. 20). Foundation Press. https://rb.gy/fywqlx
Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics.* Pearson. 0134790545.pdf (pearsonhighered.com)
Tan, T. H. (2013). Use of structural equation modeling to predict the intention to purchase green and sustainable homes in Malaysia. *Asian Social Science, 9*(10), 181–191. https://www.ccsenet.org/journal/index.php/ass/article/view/29417
The United Arab Emirates' Government (2021). *Expatriates buying a property in the UAE.* https://u.ae/en/information-and-services/moving-to-the-uae/expatriates-buying-a-property-in-the-uae
The United Arab Emirates' Government (2022a). *Golden visa.* https://u.ae/en/information-and-services/visa-and-emirates-id/residence-visas/golden-visa
The United Arab Emirates' Government (2022b). *Residence visa for the retired.* https://shorturl.at/uvzG4
White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: Journal of the Econometric Society, 48*(4), 817–836. http://www-2.rotman.utoronto.ca/~kan/3032/pdf/GeneralizedMethodOfMoments/White_Econometrica_1980.pdf
Zeileis, A., & Hothorn, T. (2002) Diagnostic checking in regression relationships. *R News.* https://journal.r-project.org/articles/RN-2002-018/RN-2002-018.pdf

Appendix A

Survey Questionnaire Informed Consent

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Informed Consent

Title of Study

A study about factors influencing the real estate purchasing intention of the expatriates in Dubai.

Purpose of Study

The purpose of the proposed study is to identify the factors which are influencing the residential real estate purchasing intentions of the expatriate in Dubai.

Study Procedures

It's a descriptive quantitative study where the researcher will use the pre-developed questionnaire of a similar study which has been conducted in Saudi Arabia and published in 2015.
The questionnaire will be electronically administered to the target population to get their responses which will be further consolidated for analysis and answering the research questions.

Risks to Participants

There is no risk to the participant by participating in the study. Your valuable responses will help the researcher complete this study successfully. The participants' responses will be kept confidential and no personal data is collected in the research. Please be assured that your answers are anonymous, your identity will not be disclosed. Your responses shall be kept confidential and results will be used only for academic purpose. The data will be analyzed on aggregate basis for this study purpose.

Benefits

The research will be beneficial to participants in following ways:

1. The study will provide an opportunity to identify the factor influences expatriates who work or live in Dubai towards purchasing real estate property in Dubai
2. It will help the governmental organizations and regulatory bodies to analyze those factors for further enhancement to the real estate industry.

Confidentiality

The responses to this research study should be anonymous. study will not collect personal information such as name or date of birth etc. so as to keep the participants anonymity. All data file received will be coded and analyzed on aggregate level, also to safeguard and protect the participants confidentiality data will be password protected so that no one except the researcher can access it. After the use of information, the files will be discarded.

Contact Information

Should you have any questions, concerns, or clarifications regarding the survey or your right to participate in the survey, please do not hesitate to contact me at Amr.moawad@westcliff.edu

Voluntary Participation
Your help with this research is strictly voluntary. It is your choice to take part in this research there is no incentives or rewards or any implied pressure to participate in the study.

Principal Investigator
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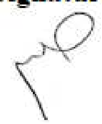

Consent

By completing the online survey, I understand that I will be participating in the study, I freely consent to participate in this study. I've read, comprehended, and had a chance to ask questions about the material offered. I know that my participation is as a volunteer and that I am free to stop anytime.

Participant Signature ....

Date ....../....../ 2022

Appendix B

Survey Questionnaire

Questionnaire Part 1 – Demographics of Participants

SURVEY QUESTIONNAIRE	
Instructions: Please indicate your response to the following questions by ticking the appropriate choice This section of the survey contains a list of information about you as participant in the survey. Please check (x) the appropriate choide which describes yourself, but please fill in only one response for each item and please respond to all of the items. If you need to change an answer, make an error and then circle your true response again.	
Part I - Demographic Information	
Age (Years)	Below 18 ( ) 18-30 ( ) 31-40 ( ) 41-59 ( ) 60 or above ( )
Gender	Male ( ) Female ( )
Marital Status	Single ( ) Married ( ) Other( )
Number of family members in UAE	1 ( ) 2 ( ) 3 ( ) 4 ( ) 5 or above ( )
Citizenship	Emirati ( ) Expatriate ( )
Education	Primary level ( ) Secondary level ( ) Diploma ( ) Bachelor ( ) Post graduate ( ) Professional qualification ( )
Occupation	Unemployed ( ) Retired ( ) Self-employed ( ) Government employee ( ) Private sector ( ) Others ( )
Monthly Income	Below AED 10,000 ( ) AED 10,000 or above ( ) AED 15,000 or above ( ) AED 18,000 or above ( ) AED 20,000 or above ( ) AED 25,000 or above ( )

Questionnaire Part 2 – Participants' View of Purchasing Real Estate

Part II - Your view of purchasing real estate

Instructions:

Please indicate your response to the following questions by ticking the appropriate choice

This section of the survey contains a list of statements that ask about your opinion of the purchasing of real estate property in Dubai.

Please check (x) the appropriate number you actually believe is closest to your response to each statement using the scale below, with 1 being 'strongly disagree' through to 5 being 'strongly agree'.

There are no right or wrong answers, but please fill in only one response for each statement and please respond to all of the statements.

If you need to change an answer, make an error and then circle your true response again.

(1) Strongly Disagree (2) Disagree (3) Neutral (4)Agree (5) Strongly Agree	STRONGLY DISAGREE	DISAGREE	NEUTRAL	AGREE	STRONGLY AGREE
Factor 1: Attitude	**1**	**2**	**3**	**4**	**5**
Buying property in Dubai is a beneficial decision					
Buying property in Dubai is a good idea					
Buying property in Dubai is a wise decision					
Buying property in Dubai is an admired decision					
Factor 2:Subjective norms	**1**	**2**	**3**	**4**	**5**
My family thinks that I should buy property in Dubai					
My family would want me to buy property in Dubai					
My family agrees with me to buy property in Dubai					
My family thinks that buying property in Dubai is a wise decision					
Factor 3: Perceived behavior control	**1**	**2**	**3**	**4**	**5**
I have enough opportunity in making a decision to buy property in Dubai (I have easy access to the market)					
I have enough time to make a decision to buy property in Dubai					
I have enough money to buy housing to buy property in Dubai					
I have enough skills and knowledge about real estate to make my own decision, If I would like to buy a property in Dubai.					
I have complete control over buying a property in Dubai					
Factor 4: Intention to Purchase Real estate	**1**	**2**	**3**	**4**	**5**
I will continue to buy property in Dubai in the future					
I intend to buy property in Dubai frequently in the future					
I plan to buy property in Dubai					
I will try to buy property in Dubai					
I want to buy property in Dubai					

Decision-Making Processes Used by Florida Hospital Administrators to Reduce 30-Day Readmission

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Abstract

Hospital administrators face a complex decision-making process in addressing 30-day readmission. This qualitative descriptive study used purposive sampling with criteria to identify and interview 12 study hospital administrators in Florida. Semi-structured interviews and 15 secondary-archival data sources were analyzed to determine themes. Ten themes emerged from the thematic data analysis, revealing that hospital administrator decision-making is multi-faceted and involves knowledge of systems, complexity, past experiences, and available data. Internal and external factors can influence hospital behavior and, if not managed correctly, can lead to chaotic readmission processes with increased operating costs, poorer patient outcomes, and unwanted attention from regulators. This study provides new knowledge to enhance hospital administration decision-making.

Keywords: hospital readmission, hospital administration, decision-making, complex adaptive systems, complexity theory, decision science

Introduction

In response to increasing health care costs in the United States (US), the US Congress passed the Patient Protection and Affordable Care Act (PPACA) in 2010 (111th United States Congress, 2010). Under the PPACA, the Hospital Readmissions and Reduction Program (HRRP) was implemented by the Centers for Medicare and Medicaid Services (CMS). Reducing hospital readmission is essential for acute care hospitals. During Fiscal Year 2017, CMS estimated over 11 million inpatient hospital discharges in the Medicare fee-for-service program, generating $135 billion in payments (Evans et al., 2021). Out of this total, excessive readmission for patients within 30 days of initial hospital discharge costs Medicare approximately $23 billion (Evans et al., 2021). This amount is significant given the low operating margins of many hospitals.

Hospital administrator decision-making is crucial for reducing readmission. The role of hospital administrators is to deliver results by implementing policies and decisions set forth by the board of directors, managing operations, and reporting performance (Goldstein & Weinstein, 2020). Hospital administrator decision-making occurs by making choices and reaching agreements within the context of approved policy (Goldstein & Weinstein, 2020). Administrators' non-clinical decisions comprise five categories: budget, resource allocation, technology acquisition, service additions and reductions, and strategic planning (Shahid et al., 2019). How funds flow through a healthcare organization can, directly and indirectly, affect the quality of patient care (Tello et al., 2020). The decision-making process of hospital administrators deserves further research.

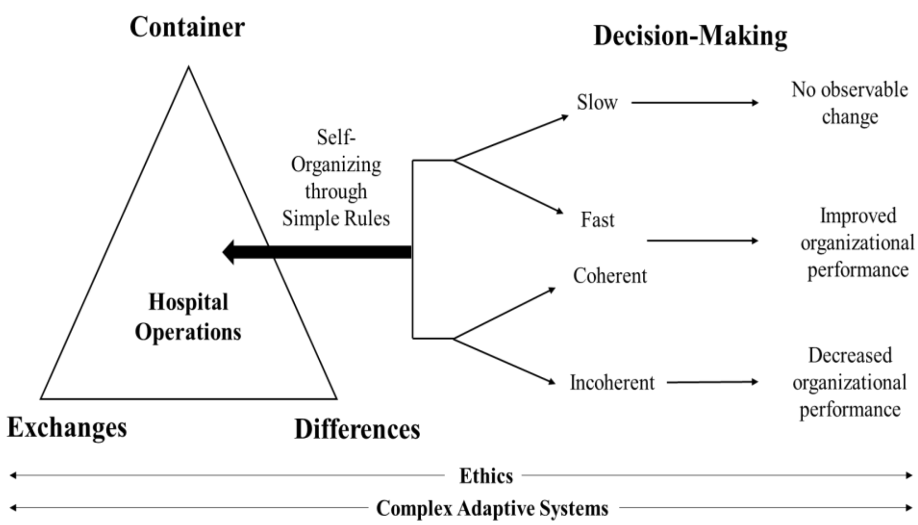
Literature Review

Previous research focused either on the results of the HRRP or the approaches used to reduce readmission. There has been less focus on the decision-making process used by hospital administrators. Research on hospital administrator decision-making stressed the use of case-based (Glette et al., 2018; Gu et al., 2019), multi-attribute (Şahin et al., 2019), or evidence-based management (Innis et al., 2020) approaches. However, these decision-making approaches do not accurately describe hospital administrators' decisions concerning 30-day readmission and healthcare complexity.

Complexity can influence both individual and organizational behaviors. Complexity can cause confusion or procrastination by affecting the decision-making process and the individual's cognitive activity (Julmi, 2019). Increasingly, complexity theory is used to explain and understand complicated health-system behaviors (Gear et al., 2018). Under complex adaptive systems, all readmissions are not considered equal, and reducing readmission requires hospitals to acknowledge that care transition plans must address socially and medically diverse patients (Connors et al., 2019). Complexity has a profound effect on healthcare decision-making.

The phenomenon of inquiry for this study concerned hospital 30-day readmission for administrators in Florida. The Container – Differences – Exchanges conceptual framework by Mennin and Eoyang (2022) and complexity science are the foundation for hospital administrator decisions and actions for 30-day readmissions (Figure 1).

Figure 1
Self-Organizing and Decision Model



Note. Model adopted from Mennin and Eoyang (2022). CDE Model of organizing in human systems. Figure created by [redacted].

Three meta-variables — Containers, Differences, and Exchanges (CDE) influence the speed, path, and direction of self-organizing systems and decision-making (Mennin & Eoyang, 2022). A container bounds the system and is a necessary condition for self-organizing processes and focuses attention; difference correlates with the intensity of the disparity inside the container; and exchanges create the connections, relationships, and tensions that provide the system with resources like energy, material, or information (Xue et al., 2022). These meta-variables can affect an organization's behavior and response to challenges or opportunities.

A research gap emerged from the literature regarding how healthcare administrators described decision-making regarding reducing 30-day readmission (Ferdinand et al., 2019; Hoffman & Yakusheva, 2020; Pennathur & Ayres, 2018). Two research questions materialized from the literature review. First, how do Florida hospital administrators make decisions to address 30-day readmission? Second, how do Florida hospital administrators describe the complexities of decision-making to address 30-day readmission?

Insights into these research questions could help understand hospital administrators' decision-making process regarding 30-day readmission, leading to improved decision-making, and lowering hospital readmission. The purpose of this qualitative descriptive study is to explore the decision-making processes used by Florida hospital administrators to address 30-day readmission.

Methods and Materials

The qualitative methodology is most appropriate for this study. Qualitative researchers desire to shift authority to participants selected as experts on the phenomenon (Babchuk, 2019). The qualitative methodology focuses on making sense of lived experiences and observed phenomena in a specific context with selected individuals (Johnson et al., 2019). Through the lens of hospital administrator decision-making, the qualitative methodology added value to the study by explaining how decisions are made and why and the generation of new knowledge.

The quantitative, and consequently, the mixed-method methodologies were not considered for several reasons. First, the basis for quantitative research is positivism, which maintains only one truth: objective reality exists independent of human perception (Sale et al., 2002). Qualitative research takes on a constructivist perspective and views knowledge as subjective, constructed through interaction, and inseparable from those who study a phenomenon (TalkadSukumar & Metoyer, 2019). Second, quantitative research relies on numeric data and statistical testing of hypotheses to examine influences between variables to answer research questions numerically (Queirós et al., 2017). The quantitative methodology cannot ascertain deeper meanings and explanations of how people interpret events (Rahman, 2020). Numeric data and hypotheses testing were not appropriate for this study because the study aims to explore the decision-making processes used by Florida hospital administrators to address 30-day readmission.

A qualitative descriptive design (QDD) is used when there is a lack of clarity about a phenomenon. A QDD versus ground theory, case study, narrative, or phenomenology is appropriate for research. There are varying perspectives on 30-day readmission. Hospital administrators in Florida represent the target population for this study. Each administrator must consider factors that can complicate readmission and make decisions that balance healthcare quality and economics. A QDD is designed to understand and describe a phenomenon and is most relevant where information is required directly from those experiencing the phenomenon (Bradshaw et al., 2017). The QDD is useful in producing a summary in everyday, factual language that facilitates understanding the phenomenon (Colorafi & Evans, 2016). Also, like other qualitative designs, there are no clear boundaries with a QDD (Kim, 2016). The lack of limits can enable researchers to obtain rich data and produce a comprehensive data summary through various data collection and analysis approaches to answer the research questions (Kim, 2016). Using a qualitative descriptive design will help develop rich data to gain insights into hospital administrators' decision-making processes and the factors that influence these decisions.

The conceptual framework and research questions guided the sampling approach. Purposive sampling was used to delimit and narrow the study population (Doyle et al., 2019). Purposive sampling provides better matching of the sample to the study's objectives, thus improving the rigor of the research and the trustworthiness of the data and results (Campbell et al., 2020). The purposive sampling method involved identifying and selecting exceptionally knowledgeable individuals about 30-day readmission (Palinkas et al., 2013). Purposive sampling facilitated the generation of rich and thick data concerning hospital administrator decision-making concerning 30-day readmission.

Twelve semi-structured interviews from Florida hospital administrators and 15 documents of archival decision-making training materials from interview participants were used to generate qualitative data regarding 30-day readmission. The generation of data from archival secondary decision-making materials offered insights into the decision-making process and the associated complexities.

A thematic analysis procedural guide by Terry et al. (2017), co-authored by Braun and Clarke, directed the data analysis. The guide consisted of the following steps: (1) familiarity with the data, (2) generating initial codes, (3) searching for themes, (4) reviewing, defining, and naming themes, and producing findings. Thematic analysis is appropriate for this qualitative descriptive study because the research on hospital administrators' decision-making process is disjointed and fragmented. Few studies on this phenomenon provide a holistic view of hospital administrator decision-making.

Several qualitative content analysis (QCA) approaches were consolidated into one protocol (O'Leary, 2017; Ruggiano & Perry, 2017; Vaismoradi & Snelgrove, 2019) to analyze archival data. The steps in the QCA process included (1) identifying biases and noting overall impressions that could influence the review of the data; (2) including information in the analysis that helps provide answers to the research question; (3) condensing codes and identifying themes; (4) comparing how the themes interact with the ones developed from the review of the literature; (5) constructing the narrative; and (6) making conclusions from the data and link the findings back to the study's research questions. All data were uploaded into MAXQDA for coding and analysis.

Results

The data analysis identified five participant themes to support research question one – How do Florida hospital administrators decide to address 30-day readmission? Each finding provided reinforcement and context to research question one by offering insights into the hospital administrator's decision-making process regarding 30-day readmissions. The literature review findings strengthened the participant themes from the interviews and the secondary archival data.

Theme 1. Clinical and Administrator Decision-Making are Complementary

Physicians and administrators use similar decision-making tools, albeit in different formats. Administrators use evidence-based management as an offshoot of evidence-based medicine (Rynes & Bartunek, 2017). Cased-based reasoning used by physicians supports administrators' case-based decision-making method (Craw, 2017). Administrator and physician decision-making regarding hospital 30-day readmissions use equivalent data for different purposes. Administrators use the data to focus on hospital operations, while physician decision-making is patient focused.

Theme 2. Technology and Data Analytics Support Readmission Decision-Making

Both physicians and administrators use predictive models to determine a patient's risk score and ascertain patient needs. Hospitals have enormous amounts of data in multiple different formats. Predictive accuracy is crucial. However, refinements are still needed in modeling to reach the potential of predictive models. Li et al. (2020) found that building cases and predicting 30-day readmission have delivered poor predictive results. Löw et al. (2019) noted the main issue with case-based reasoning to be the corruption of many healthcare datasets by missing data, making mining data suspect. Also, there are challenges in dealing with many potential predictor variables in an electronic health record (Fejza et al., 2018). Because of issues with predictive modeling, physicians and administrators should still consider their experiences as part of the decision-making process.

Theme 3. Teamwork is Essential to Readmission Decision-Making

Administrators play a critical role in creating a climate encouraging teamwork. Because of their non-linear interdependencies, hospitals have many variables not routinely distributed. According to Pype et al. (2018), characteristics supporting describing hospital units as complex include: (1) team members are interdependent, (2) interactions between team members can produce unpredictable behavior and can generate new behavior, (3) it is impossible to always to predict the action resulting from the exchanges, and (4) minor changes in variables can have significant impacts under other conditions. Each of these factors can produce different outputs and create conditions of nonlinearity that hospital administrators address.

Theme 4. Rules and Policies Provide Guardrails for Readmission Decision-Making

Simple rules bring clarity and focus to decision-making. Hospital administrator decision-making is complicated. Demanding situations characterized by many rules often require substantial knowledge to act (Le Bris, 2019). Meta, or simple, guidelines can give administrators an overall picture of events to make decisions in regulated environments like healthcare. Simple rules are shortcuts that help individuals process information (Mufarrige & Zywicki, 2020). Also, simple rules can help guide employees through uncertainty and help them make sense of situations (Kieran et al., 2021). The use of simple rules is instrumental in streamlining the decision-making process.

Policies and procedures affect hospital readmissions and provide additional structure for decision-making. Policies form the administrative guidelines for hospital decision-making. Hospital administrator decision-making occurs by making choices and reaching agreements within the context of approved policy (Goldstein & Weinstein, 2020). Simple rules, policies, and procedures help establish the boundaries of the hospital readmission container under the CDE framework.

Theme 5. Readmission Strategies Represent Choices

Making the optimal choice between different options is part of the hospital administrator's decision-making process. However, there is more to decision-making for hospital administrators than identifying choices. Administrators manage the trade-offs by controlling costs, improving patient care quality, and cultivating a safe patient environment. For example, patient readmission represents a complex issue that can adversely affect other patient care quality indicators like the length of hospital stay and mortality. These tradeoffs require administrators to balance multiple variables to achieve optimal outcomes for the hospital. Hospitals should review each readmission from multiple perspectives.

Research Question 2 pertains to how Florida hospital administrators described the complexities of decision-making to address 30-day readmission. Six themes generated from the data analysis pertain to this research question. Understanding the complexities associated with decision-making can help identify novel approaches to address 30-day readmissions or enhance existing ones.

Theme 6. Numerous Factors Converge to Make Readmission Decision-Making Complex

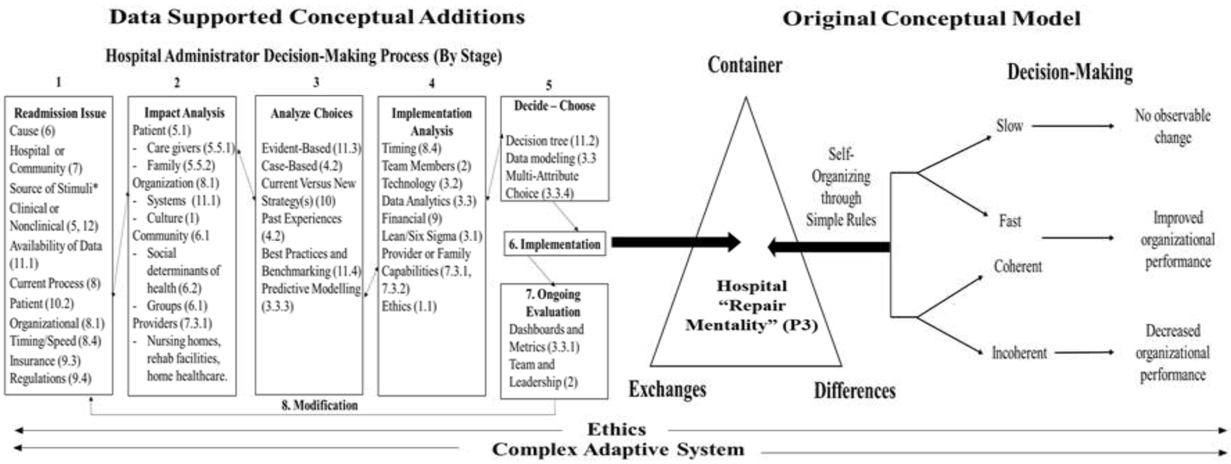
Medical complexity, like therapies and treatments, social determinants of health, and chronic health conditions, increase the issues associated with readmissions. Hospital complexity increases because diverse patient populations can access care on their terms. Deciding which readmission strategies to use is complicated, given the influence of social and medical complexities. Changes in medicine, culture, and society have necessitated a hospital's need to change its behavior and adapt (Di Sivo & Balducci, 2019). These complexities affect treatments, decision-making, internal operations, and predictive modeling.

Theme 7. The Readmission Process is Simple on the Surface but Complex in the Details

Decision-making is an inherently complex and vital function of administrators. At the heart of decision-making is choosing between alternatives (Chisengantambu-Winters et al., 2020). Guo (2020) suggested a six-step linear approach to decision-making for hospital administrators: (1) define the problem; (2) establish the criteria; (3) consider all the alternatives; (4) identify the best option; (5) develop and implement a plan of action, and (6) evaluate and monitor the solution and feedback. The steps in Guo's (2020) model align with the steps in a new decision-making model that emerges (Figure 2). However, the critical difference is that the Guo model does not consider the nonlinearity associated with readmission decision-making.

Figure 2

Emerging Readmissions Decision-Making Framework



Note. The model was adopted from Mennin and Eoyang (2022). Figure created by [redacted]. Stage One reflects the code and subcode from the data analysis. *Patient, community, insurance, internal, regulatory.

The model reflects nonlinear flows of information and resources regarding readmissions. Complex adaptive systems demonstrate nonlinearity (Braithwaite et al., 2020). Nonlinearity represents variability in a system. It is impossible to consistently predict the action resulting from the exchanges, especially in the case of readmissions, and minor changes in variables can have significant impacts under other conditions (Pype et al., 2018). Administrators should always think in terms of systems when making decisions.

Theme 8. Readmission Complexity Manifests Itself in the Cost of Poor Quality and Finances

Readmissions can increase hospital operating costs. Administrators consider hospital readmissions a quality measure. Quality is significantly associated with the higher financial viability of hospitals (Onder et al., 2021). For an average hospital, avoiding one readmission could result in reimbursement gains of $10,000 to $58,000 for Medicare discharges (Yakusheva & Hoffman, 2018). Because of complicated cost frameworks, including diagnostic coding variations, the HRRP's success is challenging to evaluate (Press et al., 2019). Given the possible financial implications of diagnostic codes, hospital administrators should consider these codes when considering interventions.

Theme 9. Patients Share Responsibility for Readmission and the Added Complexities

Patient factors like engagement, self-control, management, communication, and culture affect readmissions. Clinicians cannot control patient factors once they leave the hospital. If patients do not follow the discharge instructions and education materials and go back to their everyday lives, not only could the patients' health suffer, but the hospital could also increase its operating costs. An example of this dynamic in action is medication nonadherence. Medication adherence for diabetes, heart failure, hyperlipidemia, and hypertension could save Medicare fee-for-service $13.7 billion annually and avoid over 100,000 emergency department visits and seven million inpatient hospital days yearly (Lloyd et al., 2019). Patient noncompliance may increase healthcare costs to both society and hospitals.

Patient behaviors can influence readmissions. The viewpoints of administrators in this study and the findings from previous studies revealed three interconnected patient factors that affect readmission — engagement, self-control and management, and communication and culture. Smeraglio et al. (2019) concluded that the gap between providers' and patients' hospital discharge perspectives is a contributing root cause of preventable readmissions.

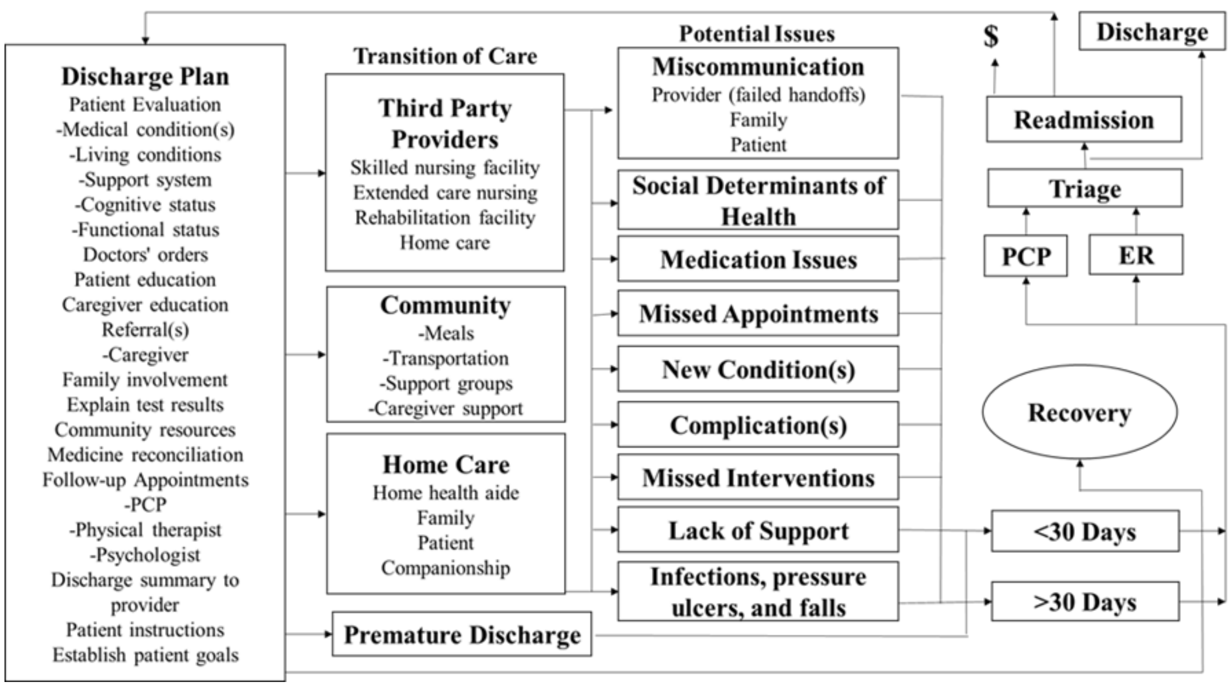
Theme 10. The Stresses and Strains of Readmission Complexity

A chronic stressor is a term that describes hospital readmissions. Chronic stressors are repetitive disruptors of everyday operations (Kagwanja et al., 2020). A complex adaptive system, like a hospital, responds differently, and sometimes in unexpected ways, to a chronic stressor. Complexity generates unpredictability. Figure 3 demonstrates the complexities associated with readmissions. Readmission is a chronic stressor that requires a team approach to management.

Patients can choose when they want to access a hospital's services. As a result, complex systems, like hospitals, are open systems that can self-organize their structural configuration by exchanging information and resources to transform and support action (Glover et al., 2020). In a complex adaptive system like a hospital, changes in one part of a system can influence other parts of the organization (Mihm et al., 2003). These stressors can cause hospitals to change structures (Di Sivo & Balducci, 2019). Failure to adapt could cause downstream harm to patients and the hospital.

Figure 3

Readmissions Process Complexity



Note. Figure created by [redacted], based on the findings and codes used in the data analysis from the research study.

Implications

Hospital administrators can use the findings from this qualitative descriptive study to make better decisions and reduce 30-day hospital readmissions. The practical implications of this study are outlined in Table 1.

Table 1
Practical Implications for Theme Findings

Theme	Practical Implication(s)
1: Clinical and administrator decision-making are complementary.	Understanding the similarities and differences in administrative decision-making processes can enhance decision-making and help bridge potential communication barriers. This dynamic can boost teamwork.
2: Technology and data analytics support readmission decision-making.	Predictive modes are not perfect. Incorporating past experiences as part of the decision-making process can enhance decision-making.
3: Teamwork is essential to readmission decision-making.	Making decisions entails assembling individuals in teams to discuss ideas. Multiple individuals within a hospital can look at the same data and form different conclusions.
4: Rules, policies, and ethics provide the guardrails for readmission decision-making.	Hospitals are highly regulated. Understanding the decision-making guardrails can help administrators minimize practices that could harm patients or the hospital.
5: Readmission strategies represent choices.	Administrators should remain aware that choosing a discharge strategy can either amplify or dampen the downstream effect of readmission in a hospital (e.g., the emergency room).
6: Hospital readmissions are a byproduct of complexity.	Hospital administrators should keep system interactions in mind when making decisions.
7: The readmission process is simple on the surface but complex in the details.	Understanding the details and dynamics in the emergent decision-making model can support hospital administrators' decision-making.
8: Readmission complexity manifests itself in hospital finances.	Earnings lost because of readmission complexity limits a hospital's ability to operate. Focusing on administrative expenditures can help hospital administrators stabilize or reduce operating costs.
9: Patients share responsibility for readmission and the added complexities.	Administrators must help their hospitals move beyond the repair dynamic and strive to get to the root causes of patient readmission. Doing so requires active involvement in their community. Community health needs assessments can help uncover opportunities.
10: The stresses and strains of readmission complexity.	Chronic stressors like readmission could adversely affect their hospital from a practice perspective (e.g., nurse and physician burnout).

There are several opportunities for future research. Future researchers could consider how executives in other regions/areas of the US describe their decision-making process and the associated complexities with 30-day readmissions. Expanding this research to other areas within the US may lead to different insights and add to the findings. Second, although purposive sampling was used, the study participants were mostly senior-level administrators. Expanding the descriptive research to mid-level administrators in Florida could lead to insights into decision-making and the associated complexities. Participants identified the impact of COVID-19 on readmissions. A third research opportunity emerged concerning how COVID-19 added complexity to hospital and readmission decision-making.

Conclusion

This qualitative descriptive study explored the decision-making processes used by Florida hospital administrators to address 30-day readmission. The research problem involved identifying the factors that add to the complexities of patient care and the complications associated with hospital administrators' 30-day readmission decision-making. Complexity in health care is a multi-faceted construct. Thirty-day hospital patient readmission is associated with various patient-related factors, including medical complexity in chronic disease, patient age, and socio-demographic characteristics. Changes in medicine, culture, patient needs, and society have necessitated a hospital to change its behavior and adapt rapidly.

By reducing readmissions, administrators can reduce hospital expenditures. This outcome can make more resources available for other areas. Reducing 30-day readmission benefits hospitals, patients, and society. Patients do not want to come back to a hospital for more treatment. Providing patients with the tools and resources can help reduce readmissions and bolster patient satisfaction. Overall, hospital administrators can use the findings from this qualitative descriptive study to make better decisions and reduce 30-day hospital readmissions.

References

Babchuk, W. A. (2019). Fundamentals of qualitative analysis in family medicine. *Family Medicine and Community Health, 7*(2), e000040. https://doi.org/10.1136/fmch-2018-000040

Begun, J. W., & Jiang, H. J. (2020). Health care management during Covid-19: Insights from complexity science. *NEJM Catalyst Innovations in Care Delivery, 1*(5). https://doi.org/10.1056/CAT.20.0541

Braithwaite, J., Glasziou, P., & Westbrook, J. (2020). The three numbers you need to know about healthcare: The 60-30-10 challenge. *BMC Medicine, 18*(1). https://doi.org/10.1186/s12916-020-01563-4

Campbell, S., Greenwood, M., Prior, S., Shearer, T., Walkem, K., Young, S., Bywaters, D., & Walker, K. (2020). Purposive sampling: Complex or simple? Research case examples. *Journal of Research in Nursing, 25*(8), 652-661. https://doi.org/10.1177/1744987120927206

Chisengantambu-Winters, C., Robinson, G. M., & Evans, N. (2020). Developing a decision-making dependency (DMD) model for nurse managers. *Heliyon, 6*(1), e03128. https://doi.org/10.1016/j.heliyon.2019.e03128

Connors, J. D. N., Binkley, B. L., Graff, J. C., Surbhi, S., & Bailey, J. E. (2019). How patient experience informed the SafeMed Program: Lessons learned during a Health Care Innovation Award to improve care for super-utilizers. *Healthcare, 7*(1), 13-21. https://doi.org/10.1016/j.hjdsi.2018.02.002

Craw, S. (2017). Case-based reasoning. In C. Sammut & Webb, G.I. (Eds.), *Encyclopedia of Machine Learning and Data Mining* (pp. 180-188). Springer. https://doi.org/10.1007/978-1-4899-7687-1_34

Di Sivo, M., & Balducci, C. (2019). Patient-centered care approach: Strategies for healing gardens. *Journal of Civil Engineering and Architecture, 13*(12), 740-751. https://doi.org/10.17265/1934-7359/2019.12.002

Doyle, L., McCabe, C., Keogh, B., Brady, A., & McCann, M. (2019). An overview of the qualitative descriptive design within nursing research. *Journal of Research in Nursing, 25*(5), 443–455. https://doi.org/10.1177/1744987119880234

Escobar, G. J., Plimier, C., Greene, J. D., Liu, V., & Kipnis, P. (2019). Multiyear rehospitalization rates and hospital outcomes in an integrated health care system. *JAMA*

Network Open, 2(12), e1916769. https://doi.org/10.1001/jamanetworkopen.2019.16769
Evans, W. N., Kroeger, S., Munich, E. L., Ortuzar, G., & Wagner, K. L. (2021). Reducing readmissions by addressing the social determinants of health. *American Journal of Health Economics, 7*(1), 1-40. https://doi.org/10.1086/711725
Fejza, A., Geneves, P., Layaida, N., & Bosson, J. (2018, October 01-03). Scalable and interpretable predictive models for electronic health records. *2018 IEEE 5th International Conference on Data Science and Advanced Analytics* (DSAA). Turin, Italy. https://doi.org/10.1109/dsaa.2018.00045
Ferdinand, A. O., Cheon, O., Bako, A. T., & Kash, B. A. (2019). Interventions aimed at addressing unplanned hospital readmission in the US: A systematic review. *Journal of Hospital Administration*, *8*(1), 16-26. https://doi.org/10.5430/jha.v8n1p16
Florida Hospital Association. *(2022). FHA'S 2022 Annual Report.* https://www.fha.org/FHA/FHA/Data-and-Research/Data-Research.aspx
Gear, C., Eppel, E., & Koziol-McLain, J. (2018). Advancing complexity theory as a qualitative research methodology. *International Journal of Qualitative Methods, 17*(1), 160940691878255. https://doi.org/10.1177/1609406918782557
Glette, M. K., Kringeland, T., Røise, O., & Wiig, S. (2018). Exploring physicians' decision-making in hospital readmission processes - a comparative case study. *BMC Health Services Research, 18*(1). https://doi.org/10.1186/s12913-018-3538-3
Glover, W. J., Nissinboim, N., & Naveh, E. (2020). Examining innovation in hospital units: A complex adaptive systems approach. *BMC Health Services Research*, *20*(1), 1–12. https://doi.org/10.1186/s12913-020-05403-2
Goldstein, S., Weinstein, J. (2020). The role of the hospital board of trustees in ensuring quality care. In D. Salem (Ed.) *Quality measures* (pp. 181-199). Springer. https://doi.org/10.1007/978-3-030-37145-6_12
Gu, D., Deng, S., Zheng, Q., Liang, C., & Wu, J. (2019). Impacts of case-based health knowledge system in hospital management: The mediating role of group effectiveness. *Information & Management, 56*(8), 103162. https://doi.org/10.1016/j.im.2019.04.005
Guo, K. L. (2020). DECIDE: A decision-making model for more effective decision making by health care managers. *The Health Care Manager, 39*(3), 133-141. https://doi.org/10.1097/hcm.0000000000000299
Hoffman, G. J., & Yakusheva, O. (2020). Association between financial incentives in Medicare's Hospital Readmissions Reduction Program and hospital readmission performance. *JAMA Network Open, 3*(4), e202044. https://doi.org/10.1001/jamanetworkopen.2020.2044
Hsuan, C., Carr, B. G., Hsia, R. Y., & Hoffman, G. J. (2020). Assessment of hospital readmissions from the emergency department after implementation of Medicare's Hospital Readmissions Reduction Program. *JAMA Network Open, 3*(5), e203857. https://doi.org/10.1001/jamanetworkopen.2020.3857
Innis, J., Barnsley, J., Berta, W., & Daniel, I. (2020). Do hospital size, location, and teaching status matter? Role of context in the use of evidence-based discharge practices. *International Journal of Healthcare Management*, *14*(4), 1011-1017. https://doi.org/10.1080/20479700.2020.1725716
Johnson, J. L., Adkins, D., & Chauvin, S. (2019). A review of the quality indicators of rigor in qualitative research. *American Journal of Pharmaceutical Education, 84*(1), 7120. https://doi.org/10.5688/ajpe7120
Julmi, C. (2019). When rational decision-making becomes irrational: A critical assessment and re-conceptualization of intuition effectiveness. *Business Research, 12*(1), 291-314. https://doi.org/10.1007/s40685-019-0096-4
Kagwanja, N., Waithaka, D., Nzinga, J., Tsofa, B., Boga, M., Leli, H., Mataza, C., Gilson, L., Molyneux, S., & Barasa, E. (2020). Shocks, stress, and everyday health system resilience: Experiences from the Kenyan coast. *Health Policy and Planning, 35*(5), 522-535. https://doi.org/10.1093/heapol/czaa002
Kaplan, C. M., Thompson, M. P., & Waters, T. M. (2019). How have 30-day readmission penalties affected racial disparities in readmission: An analysis from 2007 to 2014 in five US States. *Journal of General Internal*

Medicine, *34*(1), 878–883. https://doi.org/10.1007/s11606-019-04841-x

Kash, B. A., Baek, J., Cheon, O., Coleman, N. E., & Jones, S. L. (2018). Successful hospital readmission reduction initiatives: Top five strategies to consider implementing today. *Journal of Hospital Administration, 7*(6), 16-23. https://doi.org/10.5430/jha.v7n6p16

Kieran, S., MacMahon, J., & MacCurtain, S. (2021). Simple rules for sensemaking praxis: How HR can contribute to strategic change by developing sensemaking capability in organisations. *Human Resource Management Journal*. 32, 299–320. https://doi.org/10.1111/1748-8583.12404

Kim, J. (2016). Locating narrative inquiry in the interdisciplinary context. *In Understanding Narrative Inquiry: The Crafting and Analysis of Stories as Research* (pp. 1-25). SAGE. https://doi.org/10.4135/9781071802861

Le Bris, S. (2019). Decision-making in complex environments under time pressure and risk of critical irreversibility: The role of meta rules. *M@n@gement, 22*(1), 1. https://doi.org/10.3917/mana.221.0001

Lee, J. Y., Gowen, C. R., & McFadden, K. L. (2018). An empirical study of U.S. hospital quality: Readmission rates, organizational culture, patient satisfaction, and Facebook ratings. *Quality Management Journal, 25*(4), 158-170. https://doi.org/10.1080/10686967.2018.1515523

Lloyd, J. T., Maresh, S., Powers, C. A., Shrank, W. H., & Alley, D. E. (2019). How much does medication nonadherence cost the Medicare fee-for-Service program? *Medical Care, 57*(3), 218-224. https://doi.org/10.1097/mlr.0000000000001067

Löw, N., Hesser, J., & Blessing, M. (2019). Multiple retrieval case-based reasoning for incomplete datasets. *Journal of Biomedical Informatics, 92*, 103127. https://doi.org/10.1016/j.jbi.2019.103127

Mennin, S., & Eoyang, G. H. (2022). Question storming: The power of Questions—A method to increase options for action in uncertainty. *Journal of Evaluation in Clinical Practice. 24*(4), 650-656. https://doi.org/10.1111/jep.13704

Mihm, J., Loch, C., & Huchzermeier, A. (2003). Problem–solving oscillations in complex engineering projects. *Management Science, 49*(6), 733-750. https://doi.org/10.1287/mnsc.49.6.733.16021

Mufarrige, C., & Zywicki, T. J. (2020). Simple rules for a complex regulatory world: The case of financial regulation. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3576976

O'Leary, Z., & Hunt, J. (2017). *Secondary data: Existing data, online generated data and previous studies.* In The essential guide to doing your research project (pp. 264-294). SAGE Publications.

Onder, O., Cook, W., & Kristal, M. (2021). Does quality help the financial viability of hospitals? A data envelopment analysis approach. *Socio-Economic Planning Sciences*, *79*, 101-105. https://doi.org/10.1016/j.seps.2021.101105

111th United States Congress. (2010). *Patient Protection Affordable Care Act. Public Law 111-148*. Washington, DC: United States Government Printing Office. http://www.gpo.gov/fdsys/pkg/PLAW-111publ148/pdf/PLAW-111publ148.pdf

Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2013). Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Administration and Policy in Mental Health and Mental Health Services Research, 42*(5), 533-544. https://doi.org/10.1007/s10488-013-0528-y

Pennathur, P. R., & Ayres, B. S. (2018). A qualitative investigation of healthcare workers' strategies in response to readmission. *BMC Health Services Research, 18*(1), 138. https://doi.org/10.1186/s12913-018-2945-9

Podulka, J., & Blum, J. (2020). Regulatory Changes to Medicare in Response to COVID-19. *Health Management Associates*, 1-9. https://www.healthmanagement.com/wp-content/uploads/Podulka_Blum_Medicare-COVID_ib.pdf

Press, V. G., Au, D. H., Bourbeau, J., Dransfield, M. T., Gershon, A. S., Krishnan, J. A., Mularski, R. A., Sciurba, F. C., Sullivan, J., & Feemster, L. C. (2019). Reducing chronic obstructive pulmonary disease hospital readmissions. An official American Thoracic Society workshop report. *Annals of the American Thoracic Society, 16*(2), 161-170.

https://doi.org/10.1513/annalsats.201811-755ws
Pype, P., Mertens, F., Helewaut, F., & Krystallidou, D. (2018). Healthcare teams as complex adaptive systems: Understanding team behaviour through team members' perception of interpersonal interaction. *BMC Health Services Research, 18*(1). https://doi.org/10.1186/s12913-018-3392-3
QualityNet Home. (2020). *Hospital Readmissions Reduction Program, Frequently Asked Questions - Fiscal Year 2021*. https://qualitynet.cms.gov/files/5f294d57f75e42002168c687?filename=FY2021_HRRP_FAQs.pdf
Ruggiano, N., & Perry, T. E. (2017). Conducting secondary analysis of qualitative data: Should we, can we, and how? *Qualitative Social Work, 18*(1), 81-97. https://doi.org/10.1177/1473325017700701
Rynes, S. L., & Bartunek, J. M. (2017). Evidence-based management: Foundations, development, controversies, and future. *Annual Review of Organizational Psychology and Organizational Behavior, 4*(1), 235-261. https://doi.org/10.1146/annurev-orgpsych-032516-113306
Sahin, T., Ocak, S., & Top, M. (2019). Analytic hierarchy process for hospital site selection. *Health Policy and Technology, 8*(1), 42-50. https://doi.org/10.1016/j.hlpt.2019.02.005
Shahid, N., Rappon, T., & Berta, W. (2019). Applications of artificial neural networks in health care organizational decision-making: A scoping review. *PLOS One, 14*(2), e0212356. https://doi.org/10.1371/journal.pone.0212356
Smeraglio, A., Heidenreich, P. A., Krishnan, G., Hopkins, J., Chen, J., & Shieh, L. (2019). Patient vs. provider perspectives of 30-day hospital readmission. *BMJ Open Quality, 8*(1), e000264. https://doi.org/10.1136/bmjoq-2017-000264
TalkadSukumar, P., & Metoyer, R. (2019, February 2). *Replication and transparency of qualitative research from a constructivist perspective*. OSF Preprints. https://doi.org/10.31219/osf.io/6efvp
Terry, G., Hayfield, N., Clarke, V., & Braun, V. (2017). Thematic analysis. In *The SAGE Handbook of Qualitative Research in Psychology* (pp. 17-36). SAGE Publications Ltd. https://doi.org/10.4135/9781526405555
Vaishnavi, V., Suresh, M., & Dutta, P. (2019). A study on the influence of factors associated with organizational readiness for change in healthcare organizations using TISM. *Benchmarking: An International Journal, 26*(4), 1290-1313. https://doi.org/10.1108/bij-06-2018-0161
Vaismoradi, M., & Snelgrove, S. (2019). Theme in qualitative content analysis and thematic analysis. *Qualitative Social Research, 20*(3), http://dx.doi.org/10.17169/fqs-20.3.3376
Yakusheva, O., & Hoffman, G. J. (2018). Does a reduction in readmissions result in net savings for most hospitals? An examination of Medicare's Hospital Readmissions Reduction Program. *Medical Care Research and Review, 77*(4), 334-344. https://doi.org/10.1177/1077558718795745

The Influence of English Usage on Facebook and Personality Traits on Learning Achievement

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Abstract

Facebook's rising popularity has inspired academics and teachers to investigate its potential as a setting for learning in diverse subject areas. Personality traits are crucial for foreign language learning. This small-scale quantitative study aimed to determine the possible effects of Cambodian university students' Big Five personality traits and English usage on Facebook on their English achievement referring to the scores the participants attained through English macro skills (speaking, writing, listening, and reading). The samples were 41 English as a Foreign Language (EFL) juniors at a private university. The sole research instrument was a questionnaire, classified into two sections. The first was the adopted English Usage on Facebook Inventory for Language Learning developed by Kao and Craigie (2014), and the second was the Big Five Inventory (John & Srivastava, 1999). The findings revealed that English usage on Facebook was positively associated with only two personality traits: agreeableness and openness. However, the variables, including the five kinds of personality traits and Facebook usage of English, did not significantly predict English achievement.

Keywords: English usage on Facebook, Big Five personality traits, English achievement, EFL, Facebook

Introduction

In today's world, the rapid development of technology has made it possible for individuals, particularly young generations worldwide, to communicate. Socio-technical networks are being utilized for educational reasons and are an essential element of the entertainment sector (Siemens et al., 2015). Furthermore, a growing body of empirical studies has revealed the effects of social networking sites on students' academic success, with some claiming significant influences (Astatke et al., 2021). As Farwell and Waters (2010) pointed out, it is more interesting that active learners do not show a negative attitude toward social media.

Among multiple social media platforms, Facebook, the latest communication paradigm, is the most popular social networking site globally, with over 1.91 billion people using it daily (Zephoria-Inc, n.d.). As per Cheung et al. (2011), Facebook is a widely used social networking platform among college students. The primary justifications for Facebooking are keeping in touch with their families, fostering relationships with their teachers, and creating a learning environment (Aydin, 2012). In Cambodia, a significant portion of the surge in digital adoption is attributed to Facebook (Devanesan, 2020). According to the most recent data provided by OOSGA (n.d.), released in January 2023, there are currently about 11.75 million Facebook users in Cambodia, growing at a rate of 0.91%. With approximately 54.53% of users being male and 45.47% being female, it was reported that nearly half of Cambodians (48%) stated they had used Facebook or the Internet, and five out of every six of their respondents had personal Facebook profiles (Phong et al., 2016). The aforementioned figure even accurately echoes Peou (2010), who used to envisage that the number of Cambodian Facebook users might continue to increase in tandem with the country's rising Internet user base among young people. Cambodian people (18–24 years old) who use popular devices, such as computers and smartphones, for social networking were reported to be the second-largest user group (31.5%) as of July 2023 (Napoleon Cat, n.d.).

The comprehensive review of the literature highlighted the use of social media for English language learning in Southeast Asia, which was broken down into the main themes: enhancing collaborative learning, encouraging self-directed learning, improving writing skills, and enhancing the learning experience (Mohamad, 2023). According to Phong et al. (2016), almost a third of Cambodians now read and write on the Internet, activities that were before exclusive to the classroom, since they can acquire more knowledge and improve their communication skills. It can be inferred from the above figure that Cambodian English as a Foreign Language (EFL) university students might be actively, ubiquitously, and heavily using Facebook for different purposes. One of Cambodian EFL students' intentions on Facebook can be academically relevant, such as sharing English learning resources and engaging in English learning collaboration through exchanging written comments in an English classroom group.

In the same vein, Cambodian university students have intense contact with social media, and the intensity of their usage of social media platforms can be linked to various characteristics (Martires, 2019). Academic attainment enables learners to develop their talents and capacities through educational objectives (Hakimi et al., 2011). At the same time, Kamnoetsin (2014) believed it is a truism that social media or social networking sites unavoidably influence schooling and English learning. There needs to be more research examining the intrapersonal traits of users of social networking (Wilson et al., 2009). Thus, the topic of how Facebook might influence students' English achievement should arise, especially in Cambodian education, where similar limited research has remained unchanged.

Distinctive internal and external factors (e.g., learners' motivational beliefs and personality traits) have become a center of attention among educational researchers because these are tied to a student's academic success (Sorić et al., 2017). In particular, personality traits refer to distinctions between individuals concerning cognitive, behavioral, and emotional changes (Hogan et al., 1996, as cited in Abouzeid, 2021). The American Psychological Association (n.d., sentence 1) defines a *personality trait* as "a relatively stable, consistent, and enduring internal characteristic that is inferred from a pattern of behaviors, attitudes, feelings, and habits in the individual." Over the last decade, interest in personality traits has escalated, particularly the renowned five-factor dimension related to education and students' learning (Jensen, 2015). First and foremost, the Big Five approach constitutes one of the most extensively used systems for describing personality qualities (Abouzeid et al., 2021). Substantial research studies (e.g., Busato et al., 1998; Israel et al., 2019; Geramian et al., 2012; Hakimi et al., 2011; Komarraju et al., 2009; Marcela, 2015; O'Connor & Paunonen, 2007; Paunonen & Ashton, 2001; Sorić et al., 2017) yielded some results on the role of personality traits in learning achievement.

Non-Western cultural groups needed to pay more attention to how personality influences foreign language acquisition (Kao & Craigie, 2014). An investigation into how personality impacts learning has been mounting in any case. The researcher's idea of examining an association between personality traits and English usage on Facebook with students' English learning achievement is not a novel except for being relative to the context of Cambodia, where the research studies on students' personality traits are lacking. The researcher aims to appreciate Cambodian EFL students' English learning experiences since learning differences are strongly believed to play a vital role in second language acquisition (SLA). For instance, Ehrman (1996) postulated that personality and SLA are inextricably linked. Furthermore, social media has prompted thought-provoking policymakers and educators to consider whether educational institutions should embrace social networking site as a teaching and learning tool (Yunus & Salehi, 2012). The promising results of the present study are anticipated to give new impetus to the influential role of Facebook usage and personality traits of Cambodian EFL learners in bringing about their English achievement. The knowledge gained from the implications of this study will be beneficial to students, educators, and English lecturers at the tertiary level, especially at the research site.

To this end, this study determined the possible impact of English usage on Facebook and Cambodian university students' Big Five personality traits on their English learning achievement. It attempted to address two posted questions. First, is there any correlation between personality traits and English usage on Facebook? Second, what is the factor strongly predicting English students' achievement?

Literature Review

Facebook and English Language Learning

Social media has been widely employed in education because it offers students a number of benefits in the learning process, including educational processes, communication and cooperation, and customization of learning styles (Zachos et al., 2018). Web 2.0 technologies (e.g., Facebook) were hailed by Harrison and Thomas (2009) as having the potential to revolutionize the study of foreign languages (Harrison & Thomas, 2009). Since the beginning of its official launch, Facebook has been heavily used by students as the primary reason to stay in touch with friends (Ellison et al., 2007). High-level technology use is generally linked to a student-centered or constructivist approach (Becker, 1994; Becker & Riel, 1999, as cited in Ertmer, 2005). Pedagogically, social media, such as Facebook, enhances students' learning self-regulation (Dabbagh & Kitsantas, 2012). Facebook can be employed in foreign language classes, enabling learners to be exposed to real-life language exchanges and achieve socio-pragmatic awareness and competence (Blattner & Fiori, 2009). Students formally and informally use Facebook to serve their learning purposes (Towner & Lego Muñoz, 2011).

The Big Five Personality Traits

The top level of the personality hierarchy is occupied by the Big Five personality traits, including neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness; moreover, these variables are believed to cover the whole range of more specific personality traits found at lower levels of the hierarchy (O'Connor & Paunonen, 2007). According to the previous research review by Komarraju et al. (2009), the Big Five traits correlate with various behaviors, such as learning achievement and work performance.

According to Costa and McCrae (1992), originality, curiosity, and ingenuity are qualities that define *openness*. Orderliness, responsibility, and dependability define *conscientiousness*. Talkativeness, assertiveness, and energy are characteristics of *extroversion*. Good naturedness, cooperativeness, and trust are traits related to *agreeableness*. Lastly, *neuroticism* is characterized by instability and is considered the polar opposite of emotional stability.

Personality and Foreign Language Academic Achievement

Researchers believe differences in personality traits like persistence, dependability, talkativeness, and dominance may affect how proficiently students will perform in school. Throughout the 20th century, there has been interest in the relationship between personality traits and academic achievement (O'Connor & Paunonen, 2007). Recent years have seen a sizable quantity of empirical research based on the Big Five model that sought to identify correlations between student personality traits and academic results, notably English proficiency or achievement. Different variables influence EFL students' learning assessments, including personality traits and individual variances (Asghari et al., 2012). It can be hypothesized that the influence of neuroticism and conscientiousness may also apply to particular achievements in foreign language learning (Cao & Meng, 2020). Similarly, conscientiousness was indirectly and positively connected to second language fluency (MacIntyre & Charos, 1996).

Personality and Facebook Use

An increasing amount of research suggests individual differences in the Big Five personality traits are related to various forms of Internet usage (Amichai-Hamburger & Ben-Artiz, 2003, as cited in Gilbert & Barton, 2013). The relationship between personality characteristics and network positions has only recently attracted attention. User personality type affects how people use social networking sites, according to the literature Naqshbandi et al. (2017) reported. Extraversion and openness to new experiences are two personality traits that may encourage and speed up the establishment of relationships in social networks, but neuroticism prevents people from forming relationship ties (Wehrli, 2008).

Methods and Materials

Research Design

This present study has a correlational design. Creswell (2012, p. 337) suggested correlational design to be considered to determine "relating variables or predicting outcomes," thus justifying the research objectives.

Participants

A fundamental prerequisite for the participants was that the participants must own a Facebook account and have exposure to and experience using it. It was reported that most participants (70%) have been using Facebook for at least five years, and only 30% have used it for less than five years. Most of the participants (66%) sometimes visit Facebook, and only 2.5% rarely access it. Facebook is usually visited by 17% of the participants, and 14.5% always check Facebook. The participants were 41 third-year English major students (26 females and 15 males) at a private university in Phnom Penh and comprised the total number of students enrolled for the academic year 2021–2022.

Instruments

Regarding instrumentation, a 12-item questionnaire on the English Usage on Facebook Inventory for Language Learning developed by Kao and Craigie (2014) was adopted to explore information related to students' English usage on Facebook. The first part of the survey requested demographic information from respondents (e.g., age, gender, and daily time spent on Facebook). The second part solicited students' information on how active they were in English usage activities. On a five-point Likert scale, respondents scored their level of agreement (1=*strongly disagree*; 2=*disagree*; 3=*neutral*; 4=*agree*; 5=*strongly agree*).

Regarding academic psychology, the Big Five Personality Traits are the most widely recognized and utilized personality model (Abouzeid et al., 2021). The Big Five Inventory (BFI) (John & Srivastava, 1999) is a self-reported questionnaire assessing the Big Five personality characteristics, including extraversion (eight items), agreeableness (nine items), conscientiousness (nine items), neuroticism (eight items), and openness (ten items). The 44-item BFI is scored on a five-point scale, ranging from one (*disagree* a lot) to five (*agree a lot).* The author reversed scores on some items.

Students' scores on the core English exam served as a measure of English academic achievement. Core English is a compulsory subject that exposes students to their English learning macro-skills, including speaking, listening, writing, and reading skills.

Data Collection

At the time of the investigation, there were only two classes in year three in the setting of the study. The researcher contacted the dean of the Faculty of Foreign Languages to gain official approval. Then, the researcher decided to invite all students from both classes to participate in the data collection. They were all students of the researcher, so ordinary class time was used for the instrument administration. Initially, each respondent answered a Google Form questionnaire. The researcher not only read the instructions out loud to the class but also addressed questions from the students. All samples were ethically informed, and participants served on a voluntary basis.

Data Analysis

A Pearson correlation product moment was run to determine whether there were any associations between personality traits and English usage on Facebook. Multiple regression analysis was computed to explore two aspects, including any possible influence of English usage on Facebook and personality traits on the English learning achievement and the factor that strongly predicts the English learning achievement.

Results

A Pearson correlation coefficient was computed to assess the linear relationship between personality traits and English usage on Facebook. Two personality traits were shown to be connected to Facebook usage, but not all of them. Table 1 below shows that English usage on Facebook correlated moderately with only two types of personality traits, including agreeableness (r =.479; p<.01) and openness (r =.383; p<.01). Thus, it may be suggested that for students with increasing levels of agreeableness or openness, English usage on Facebook tended to increase moderately.

Table 1

Correlation between Personality Traits and English Usage on Facebook

	1	2	3	4	5	6
1. Facebook Measurement	—	.030	.479**	.211	-.175	.383*
2. Extraversion		—	.247	.296	-.366*	.070
3. Agreeableness			—	.436**	-.251	.154
4. Conscientiousness				—	-.672**	.144
5. Neuroticism					—	.071
6. Openness						—

Multiple regression was run to predict English achievement from English usage on Facebook and the student's personality traits. These variables did not significantly predict English achievement statistically; F (7, 33) = 1.001, p >.0005, R^2 =.175. All seven variables did not contribute statistically significantly to the prediction (p > .05.) Hence, neither the Big Personality traits nor English usage on Facebook statistically predicted English learning achievement.

Discussion/Implications

Based on the results shown in Table 1, understanding how agreeableness affects English usage on Facebook is crucial. Individuals with agreeable personalities displayed being dependable, empathic, cooperative (Ross et al., 2009), and inherently altruistic (Costa & McCrae, 1992). Highly agreeable people would be more ready to utilize the internet, especially Facebook, to communicate with others (Sharma & Jaswal, 2015). Using Facebook can satisfy the urge that agreeable ones have to take care of others and foster a sense of belonging; furthermore, individuals are more motivated to show themselves socially and, thus, are more inclined to engage in online activities (Seidman, 2013). They may utilize it to maintain their informational and psychosocial demands (Naqshbandi et al., 2017). Hence, Cambodian university students tend to use English on Facebook for various functions, especially communication. In particular, according to Amichai-Hamburger and Vinitzky (2010), there was a correlation between agreeableness and posting comments on Facebook. Thus, Cambodian EFL learners may prefer to post comments in English. They may additionally be involved in English usage through other activities on Facebook, including posting statuses to express their thoughts and experiences, chatting or messaging with their friends and families, watching movies or short clips, and learning English online. All respondents experienced a period of the COVID-19 pandemic, which means they were largely and unavoidably exposed to online environments, such as virtual learning and interaction, so Facebook usage, the most popular social media platform in Cambodia, is a common site among them.

Openness measures a person's receptivity to new experiences, open-mindedness, creativity, and imagination; moreover, it describes the breadth, depth, and complexity of a person's mental and experiential life. People falling under the openness dimension are often described as original, creative, and curious (Costa & McCrae, 1992). Individuals who score highly on the openness scale are more inclined to use and stay current with new social networking platforms (Wehrli, 2008). A greater habitual behavior to interact with others on Facebook was linked to higher degrees of openness (Ross et al., 2009), and it is a personality quality affecting time spent on Facebook (Rouis et al., 2011). John and Srivastava (1999) firmly stated that curiosity and a need for novelty are signs of high openness. In contrast, a preference for convention and established patterns indicates a sign of poor openness. In 2015, Sharma and Jaswal found a useful link between using Facebook and being open to new experiences. As a result, as social media is still a relatively new use of Internet technology, people who are more open to new experiences are more inspired to create online profiles and use instant messages and videos for communication (Correa et al., 2013). From the findings, one possibility may be that Cambodian EFL learners who are open indicated a tendency to use English on Facebook, which was linked to moderate degrees of openness. They may interact with their friends to share information or ideas in English and use other useful functions of Facebook. The findings confirmed the claim of Bachrach et al. (2012), who indicated that the number of likes, groups, and status updates on Facebook are all positively connected with openness, similar to the openness traits of seeking out new things and ideas and sharing them with others. Facebooking enables them to learn new things and stay current on present events, aiding them in becoming more knowledgeable. Although social networking sites have existed for the last decade, Facebook is still seen as a groundbreaking innovation among Cambodian university students.

To some extent, the results do not support the notion that students who use English while Facebooking can facilitate their English learning. After doing a thorough literature analysis, Everson et al. (2013) asserted there were not many relevant studies that demonstrated social media's beneficial effects on education. For instance, most cases indicated students used Facebook for the purpose of informal learning opportunities. The participants may spend time on Facebook and take less time to think through and complete their academic tasks. They may engage in informal learning situations (like asking their friends about matters related to homework or assignments), or they may mostly be involved in Facebook activities that are not related to English learning but rather communication. Similarly, Facebook is viewed as a distraction from learning rather than a tool that may be supportive (Huang & Leung, 2009; Junco & Cotton, 2010; Karpinsik & Duberstein, 2009, as cited in Naqshbandi et al., 2017). English usage on Facebook may be compelling if it is pedagogically included and practiced among Cambodian students.

The statistical results indicated that all the Big Five personality traits did not influence academic achievement. Such findings were in line with a few past studies (Tus, 2019; Abouzeid et al., 2021). A plausible reason to explain it is that students may still be in the process of developing themselves (Tus, 2019). Hence, the English learning achievement of Cambodian students, which might be affected by other factors, is multifaceted.

Recommendations

First, the author could not underline Facebook's contribution to improving English achievement. The results implied that time spent on Facebook and different activities on it tended to not have any direct influence on students'

English achievement. Instead, social networking should be taken advantage of by educationally using Facebook to facilitate English learning and study-related exchange (Wodzicki et al., 2012), improving student English learning outcomes. Similarly, Barrot (2018, p. 10) recommended teachers and students "determine the fate of Facebook as a language learning environment." It may be helpful to have a greater grasp of other variables affecting Facebook use and the impact that Facebooking plays on academic success.

Second, educators, especially teachers, should consider students' personality traits in course delivery strategies, incorporating different methods that cater to learners' differences (Abouzeid et al., 2021). Classroom learning should focus on students' self-awareness of their personality traits, encouraging active participation, and optimizing learning experiences (Tus, 2019).

Conclusion

The present study aimed to add new evidence on how Cambodian undergraduate students' Big Five personality traits and English use on Facebook affect their English achievement. Indeed, one of the findings indicated personality factors to be essential in determining the level of Facebook use; however, it was explicitly discovered that not all personality traits but certain of them, including agreeableness and openness, were moderately associated with Facebook usage. Moreover, the Big Personality traits and English usage on Facebook did not significantly predict the level of English achievement. Thus, the Big Personality traits and English use on Facebook do not play a crucial role in enhancing English learning.

Limitations and Future Research

Despite its intriguing findings, the studies' imitations merit attention. First, it should be highlighted that the use of quantitative data from surveys restricted the implications that may be made from the results, so further studies should adopt mixed-methods techniques to provide in-depth information and triangulation, such as a questionnaire in conjunction with an interview or observation. Second, the number of participants in this study was small; therefore, the results cannot be generalized. Next studies should be conducted with a larger sample size to validate the findings and analyses. Finally, future researchers are recommended to conduct further research on the effects of personality traits on foreign language learners' achievement in diverse circumstances so that they can fully comprehend the significance of personality elements in English learning.

References

Abouzeid, E., Fouad, S., Wasfy, N. F., Alkhadragy, R., Hefny, M., & Kamal, D. (2021). Influence of personality traits and learning styles on undergraduate medical students' academic achievement. *Advances in Medical Education and Practice*, *12*, 769–777. https://doi.org/10.2147/AMEP.S314644

American Psychological Association. (2023). Personality trait. In *APA dictionary of psychology*.https://dictionary.apa.org/personality-trait

Amichai-Hamburger, Y., & Vinitzky, G. (2010). Social network use and personality. *Computers in Human Behavior*, *26*(6), 1289–1295. https://doi.org/10.1016/j.chb.2010.03.018

Asghari, A., Fatemi, A.H. and Pishgha, R. (2012). Attribution theory and personality traits among EFL learners. *International Journal of Linguistics*, *4*, 229–243. https://doi.org/10.5296/ijl.v4i2.1451

Astatke, M., Weng, C., & Chen, S. (2021). A literature review of the effects of social networking sites on secondary school students' academic achievement. *Interactive Learning Environments*, *29*(1), 1–17. https://doi.org/10.1080/10494820.2021.1875002

Aydin, S. (2012). A review of research on Facebook as an educational environment. *Educational Technology Research and Development*, *60*(6), 1093–1106. https://doi:10.1007/s11423-012-9260-7

Bachrach, Y., Kosinski, M., Graepel, T., Kohli, P., & Stillwell, D. (2012). Personality and patterns of Facebook usage. *Proceedings of the 4th annual ACM web science conference* (pp. 24–32). ACM. http://dx.doi.org/10.1145/2380718.2380722

Barrot, J. S. (2018). Facebook as a learning environment for language teaching and learning: A critical analysis of the literature from 2010 to 2017. *Journal of Computer Assisted Learning*, *34*(6), 863−875. https://doi.org/ 10.1111/jcal.12295

Blattner, G., & Fiori, M. (2009). Facebook in the language classroom: Promises and possibilities. *Instructional Technology and Distance Learning, 6*(1), 17−28.

Busato, V. V., Prins, F. J., Elshout, J. J., & Hamaker, C. (1998). The relation between learning styles, the Big Five personality traits and achievement motivation in higher education. *Personality and Individual Differences*, *26*(1), 129–140. https://doi.org/10.1016/s0191-8869(98)00112-3

Cao, C., & Meng, Q. (2020). Exploring personality traits as predictors of English achievement and global competence among Chinese university students: English learning motivation as the moderator. *Learning and Individual Differences*, *77*, 101814. https://doi:10.1016/j.lindif.2019.101814

Cheung, C. M., Chiu, P. Y., & Lee, M. K. (2011). Online social networks: Why do students use Facebook? *Computers in Human Behavior*, *27*(4), 1337−1343. https://doi.org/10.1016/j.chb.2010.07.028

Correa, T., Bachmann, I., Hinsley, A. W., & Gil de Zúñiga, H. (2013). Personality and social media use. In E. Li, S. Loh, C. Evans, & F. Lorenzi (Eds.), *Organizations and social networks: Utilizing social media to engage consumers* (pp. 41–61). IGI Global. https://doi:10.4018/978-1-4666-4026-9.ch003

Costa, P. T., Jr., & McCrae, R. R. (2008). The revised neo personality inventory (NEO-PI-R). In G. J. Boyle, G. Matthews, & D. H. Saklofske (Eds.), *The SAGE handbook of personality theory and assessment*, *Vol. 2. Personality measurement and testing* (pp. 179–198). Sage Publications. https://doi.org/10.4135/9781849200479.n9

Creswell, J. W. (2012). *Educational research: Planning, conducting, and evaluating quantitative and qualitative research* (4th ed.). Pearson.

Dabbagh, N., & Kitsantas, A. (2012). Personal learning environments, social media, and self-regulated learning: A natural formula for connecting formal and informal learning. *The Internet and Higher Education*, *15*(1), 3–8. https://doi.org/10.1016/j.iheduc.2011.06.002

Devanesan, J. (2020, August 07). *How Facebook has powered Cambodia's booming digitaleconomy.* Tech Wire Asia. https://techwireasia.com/2020/08/how-facebook-has-powered-cambodias-digital-economy/

Ehrman, M. E. (1996). *Understanding second language learning difficulties*. SAGE Publications, Inc., https://doi.org/10.4135/9781452243436

Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The benefits of Facebook "friends": Social capital and college students' use of online social network sites. *Journal of Computer-Mediated Communication, 12*(4). 1143–1168. https://doi.org/10.1111/j.1083-6101.2007.00367.x

Ertmer, P. A. (2005). Teacher pedagogical beliefs: The final frontier in our quest for technology integration? *Educational Technology Research and Development*, *53*(4), 25–39. https://doi.org/10.1007/BF02504683

Everson, M., Gundlach, E., & Miller, J. (2013). Social media and the introductory statistics course*. Computers in Human Behavior, 29*(5), A69–A81. https://doi.org/10.1016/j.chb.2012.12.033

Farwell. T. M., & Waters, R. D. (2010). Exploring the use of social bookmarking technology in education: An analysis of students' experiences using a course-specific delicious. Com Account. *MERLOT Journal of Online Learning and Teaching*, *6*, 398–408. https://repository.usfca.edu/pna/19/

Geramian, S. M., Mashayekhi, S., & Ninggal, M. T. B. H. (2012). The relationship between personality traits of international students and academic achievement. *Procedia - Social and Behavioral Sciences*, *46*, 4374–4379. https://doi.org/10.1016/j.sbspro.2012.06.257

Gilbert, G., & Barton, H. (2013). The motivations and personality traits that influence Facebook usage. In A. Power & G. Kirwan (Eds.), *Cyberpsychology and new media: A thematic reader* (pp. 26–37). Psychology Press.

Hakimi, S., Hejazi, E., & Lavasani, M. G. (2011). The relationships between personality traits and students' academic achievement. *Procedia - Social and Behavioral Sciences*, *29*, 836–845. https://doi.org/10.1016/j.sbspro.2011.11.312

Harrison, R., & Thomas, M. (2009). Identity in online communities: Social networking sites and language learning. *International Journal of Emerging Technologies and Society*, *7*(2), 109–124. http://www.swin.edu.au/ijets

Israel, A., Lüdtke, O., & Wagner, J. (2019). The longitudinal association between personality and achievement in adolescence: Differential effects across all Big Five traits and four achievement indicators. *Learning and Individual Differences*, *72*, 80–91. https://doi.org/10. 1016/j.lindif.2019.03.001

Jensen, M. (2015). Personality traits, learning and academic achievements. *Journal of Education and Learning*, *4*(4), 91–118. https://doi.org/10.5539/jel.v4n4p91

John, O. P., & Srivastava, S. (1999). The Big Five Trait taxonomy: History, measurement, and theoretical perspectives. In L. A. Pervin & O. P. John (Eds.), *Handbook of personality: Theory and research* (2nd ed., pp. 102-138). Guilford Press.

Kamnoetsin, T. (2014). *Social media use: A critical analysis of Facebook's impact on collegiate EFL students' English writing in Thailand*. [Doctoral dissertation, Seton Hall University]. Seton Hall University Dissertations and Theses (ETDs). https://scholarship. shu.edu/dissertations/2059

Kao, P.-C., & Craigie, P. (2014). Effects of English usage on Facebook and personality traits on achievement of students learning English as a foreign language. *Social Behavior and Personality: An international journal*, *42*(1), 17–24. https://doi.org/10.2224/sbp.2014.42.1.17

Komarraju, M., Karau, S. J., & Schmeck, R. R. (2009). Role of the Big Five personality traits in predicting college students' academic motivation and achievement. *Learning and Individual Differences*, *19*(1), 47–52. https://doi.org/10.1016/j.lindif.2008.07.001

MacIntyre, P. D., & Charos, C. (1996). Personality, attitudes, and affect as predictors of second language communication. *Journal of Language and Social Psychology*, *15*(1), 3–26. https://doi.org/10.1177/0261927X960151001

Marcela, V. (2015). Learning strategy, personality traits and academic achievement of university students. *Procedia - Social and Behavioral Sciences*, *174*, 3473–3478. https://doi.org/10.1016/j.sbspro.2015.01.1021

Martires, H. (2019). Students' engagement in social media in Cambodia. *Conhecimento & Diversidade*, *11*(23), 145–165. https://doi.org/10.18316/rcd.v11i23.5398

Mohamad, F. F. (2023). Social media use for English learning in southeast Asia: A systematic review. *Intellectual Discourse*, *31*(1), 140-161. https://journals.iium.edu.my/intdiscourse/index.php/id/article/view/1907

Napoleon Cat. (n.d.). *Facebook users in Cambodia*. https://napoleoncat.com/stats/facebook-users-in-cambodia/2023/07/

Naqshbandi, M. M., Ainin, S., Jaafar, N. I., & Mohd Shuib, N. L. (2017). To Facebook or to Face Book? An investigation of how academic performance of different personalities is affected through the intervention of Facebook usage. *Computers in Human Behavior*, *75*, 167–176. https://doi:10.1016/j.chb.2017.05.012

O'Connor, M. C., & Paunonen, S. V. (2007). Big Five personality predictors of post-secondary academic performance. *Personality and Individual Differences*, *43*(5), 971–990. https://doi.org/10.1016/j.paid.2007.03.017

OOSGA. (2023, October 30). *Social media in Cambodia – 2023 stats & platform trends*. https://oosga.com/social-media/khm/

Paunonen, S. V., & Ashton, M. C. (2001). Big Five predictors of academic achievement. *Journal of Research in Personality*, *35*(1), 78–90. https://doi.org/10.1006/jrpe.2000.2309

Peou, C. & Leu, M. (2010). Internet integration among Cambodian students: Motivations, attitudes and academic utilization. *International Journal of Emerging Technologies and Society, 9*(2), 95 – 115. https://dmc-cci.edu.kh/research/cambodia-communication-review-2010/

Phong, K., Srou, L., & Solá, J. (2016, December 14). *Mobile phones and internet use in Cambodia 2016*. The Asia Foundation.

https://asiafoundation.org/publication/mobile-phones-internet-use-cambodia-2016/

Ross, C., Orr, E., Sisic, M., Arseneault, J. M., Simmering, M. G., & Orr, R. R. (2009). Personality and motivations associated with Facebook use. *Computers in Human Behavior*, *25*(2), 578–586. https://doi.org/10.1016/ j.chb.2008.12.024

Rouis, S., Limayem, M., & Salehi-Sangari, E. (2011). Impact of Facebook usage on students academic achievement: Role of self-regulation and trust. *Electronic Journal of Research in Educational Psychology*, *9*(3), 961-994. https://doi.org/10.25115/ejrep.v9i25. 1465

Seidman, G. (2013). Self-presentation and belonging on Facebook: How personality influences social media use and motivations. *Personality and Individual Differences, 54*(3), 402–407. https://doi.org/10.1016/j.paid.2012.10.009

Sharma, A., & Jaswal, I. (2015). Personality and patterns of Facebook usage. *International Journal of Academic Research in Psychology,* *2*(2), 31–44. https://doi.10.6007/IJARP/v2-i2/2064

Siemens, G., Gašević, D., & Dawson, S. (2015). *Preparing for the digital university: A review of the history and current state of distance, blended, and online learning*. Athabasca University Press. https://eddl.tru.ca/wp-content/uploads/2018/12/PreparingDigitalUniversity-George-Siemens.pdf

Sorić, I., Penezić, Z., & Burić, I. (2017). The Big Five personality traits, goal orientations, and academic achievement. *Learning and Individual Differences*, *54*, 126–134. https://doi.org /10.1016/j.lindif.2017.01.024

Towner, T. L. & Lego Muñoz, C. (2011). Facebook and education: A classroom connection? Wankel, C. (Ed.) *Educating Educators with Social Media*: *Cutting-Edge Technologies in Higher Education, Vol. 1* (pp. 33–57). Emerald Group Publishing Limited. https://doi.org/10.1108/S2044-9968(2011)0000001005

Tus, J. (2019). The impact of the personality traits on the academic achievement of the senior high school students. *Journal of Global Research in Education and Social Science*, *13*(6), 208–212. https://doi.org/10.6084/m9.figshare.12250409.v1

Wehrli, S. (2008). *Personality on social network sites: An application of the Five Factor Model -ETH Zurich Sociology Working Papers 7*. Chair of Sociology. https://repec.ethz.ch/ets/papers/wehrli_studivz_big5.pdf

Wilson, K., Fornasier, S., & White, K. (2009). Psychological predictors of young adults' use of social networking sites. *CyberPsychology and Behaviour*, *13*(2), 173–177. http://doi.org/10.1089/cyber.2009.0094

Wodzicki, K., Schwämmlein, E., & Moskaliuk, J. (2012). "Actually, I wanted to learn": Study-related knowledge exchange on social networking sites. *The Internet and Higher Education,* *15*(1), 9–14. https://doi.org/10.1016/j.iheduc.2011.05.008

Yunus, M., & Salehi, H. (2012). The effectiveness of Facebook groups on teaching and improving writing: Students' perceptions. *International Journal of Education and Information Technologies, 6*(1), 87−96. https://research.iaun.ac.ir/pd/hadisalehi/pdfs/PaperM_7787.pdf

Zachos, G., Paraskevopoulou-Kollia, E., & Anagnostopoulos, I. (2018). Social media use in higher education: A review. *Education Sciences,* *8*(4), 194. https://doi.org/10.3390/educsci8040194

Zephoria-Inc. (n.d.). *The top 10 valuable Facebook statistics – Q2 2021*. Retrieved December 20, 2022, from https://zephoria.com/top-15-valuable-facebook-statistics/

Appendix A

English Usage on Facebook Inventory for Language Learning (Kao & Craigie, 2014)

Instruction: Please think about your experience on Facebook andread the following statements. Please indicate the extent to which each statement may or may not apply to you by answering 1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree.

1. I share my thoughts in English on Facebook.
2. I read English postings, messages, news, or articles on Facebook.
3. I write English messages or postings on Facebook.
4. I watch English videos or movies on Facebook.
5. I chat with friends in English on Facebook.
6. I post English messages on Facebook.
7. I use English to update or edit my Facebook status.
8. I make comments in English on friends' walls.
9. I use Facebook to improve my English skills.
10. I use English to describe my own photographs or my friends' photographs on Facebook.
11. I use English to write my Facebook profile.
12. I communicate in English on Facebook.

Appendix B

The Big Five Inventory (John & Srivastava, 1999)

Instruction: Read all statements and give your response to each item by clicking in the boxes that suits your opinion: 1=Disagree Strongly; 2=Disagree a Little; 3=Neither Agree nor Disagree; 4=Agree a Little; 5=Agree Strongly

I see myself as someone who...

_____1. is talkative
_____2. tends to find fault with others
_____3. does a thorough job
_____4. is depressed, blue
_____5. is original, comes up with new ideas
_____6. is reserved
_____7. is helpful and unselfish with others
_____8. can be somewhat careless
_____9. is relaxed, handles stress well
_____10. is curious about many different things
_____11. is full of energy
_____12. starts quarrels with others
_____13. is a reliable worker
_____14. can be tense
_____15. is ingenious, a deep thinker
_____16. generates a lot of enthusiasm
_____17. has a forgiving nature
_____18. tends to be disorganized
_____19. worries a lot
_____20. has an active imagination
_____21. tends to be quiet
_____22. is generally trusting

____23. tends to be lazy
____24. is emotionally stable, not easily upset
____25. is inventive
____26. has an assertive personality
____27. can be cold and aloof
____28. perseveres until the task is finished
____29. can be moody
____30. values artistic, aesthetic experiences
____31. is sometimes shy, inhibited
____32. is considerate and kind to almost everyone
____33. does things efficiently
____34. remains calm in tense situations
____35. prefers work that is routine
____36. is outgoing, sociable
____37. is sometimes rude to others
____38. makes plans and follows through with them
____39. gets nervous easily
____40. likes to reflect, play with ideas
____41. has few artistic interests
____42. likes to cooperate with others
____43. is easily distracted
____44. is sophisticated in art, music, or literature

Scoring:
BFI scale scoring ("R" denotes reverse-scored items):
Extraversion: 1, **6R**, 11, 16, **21R**, 26, **31R**, 36
Agreeableness: **2R**, 7, **12R**, 17, 22, **27R**, 32, **37R**, 42
Conscientiousness: 3, **8R**, 13, **18R**, **23R**, 28, 33, 38, **43R**
Neuroticism: 4, **9R**, 14, 19, **24R**, 29, **34R**, 39
Openness: 5, 10, 15, 20, 25, 30, **35R**, 40, **41R**, 44.

Determinants of Circular Economy: An Empirical Approach in the Context of the United States of America

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Abstract

The USA is the world's largest economy in terms of the consumption of resources. The excessive and irresponsible consumption of resources in the developed countries has jeopardized the stock of global resources. This quantitative study highlighting the importance of the circular economy (CE), has assessed the factors that would support the circular transition in the USA. Time series analysis based on the Autoregressive Distributed Lag (ARDL) model was employed to analyze the impact of Gross Domestic Product (GDP) per capita, Research and Development expenses, and Renewable Energy consumption on circular economy in the US with annual data from 1971 to 2017. While the study indicated the existence of a long-run relationship between the GDP per capita and renewable energy consumption, no relationship was observed between research and development expenses and the circular economy. The study strongly emphasizes the need for policy interventions to enhance the level of awareness regarding circular economy, increase consumption of renewable energies and steering investments in research and development activities to support CE activities in the USA.

Keywords: Circular economy, resource productivity, the USA, determinants of circular economy, quantitative, ARDL, time series analysis

Introduction

The pace at which human civilizations are consuming resources is alarming. Already, the ramification of this *extraction economy*, which focuses more on extracting virgin minerals from the earth, is observed across the globe. Obdurate and hasty quench for production and consumption (P&C) has become unsustainable, bringing numerous implications across the social, economic, and environmental domains. A philosophy of *cowboy economy,* which advocates for infinite availability of resources (Boulding, 1966; Smith, 1972) should be taken off by the *spaceship economy,* which emphasizes the cautious use of the limited amount of the earth's resources (Brown, 2004) since we are already heading towards the *dumping economy*.

The Global Resources Outlook report published by United Nations (2019) stated that resource extraction has tripled since 1970, driving up the annual global extraction of materials from 27 billion tons in 1970 to 92 billion tons in 2017. For the first time, it was over 100 billion tons (Circular Economy, 2020). As stated in United

Nations Environment report, North America and Europe has annual per capita material footprints (MF) of 25 and 30 tons, respectively, whereas it is 9 for the Asia Pacific (Mosbergen, 2016). If everybody consumes as the average person in a high-income country, we would need 3.8 Earths to sustain our survival (Hickel, 2018). This will soon create a deficit where human civilizations have to scramble for resources impacting how businesses produce, people consume, and countries trade (Circular Economy, 2020).

The circular economy, which focuses on an ethical and responsible utilization of resources is a testament to enhancing resource productivity and minimize the pressure of our hasty P&C in the limited resources left. While the circular economy CE concept has gained more traction and presence in EU countries, it is still at its infancy in the USA. Hence this study is objectified to empirically assess the impact of GDP per capita, consumption of renewable energy, and research and development expenses on the transition of the USA from the linear economy (LE) to the CE mode of P&C. The following hypotheses were setup:

Hypothesis 1: Resource productivity is positively influenced by GDP per capita.

Hypothesis 2: Resource productivity is positively influenced by renewable energy consumption.

Hypothesis 3: Resource productivity is positively influenced by research and development (R&D) expenses.

Circular Economy

Circular economy (CE) is a shift from the traditional take-make-dispose mode of production and consumption to a much more restorative and regenerative approach that emphasizes the optimum use of resources. Alhawari et al. (2021) described CE as a dual-loop regenerative system that effectively and efficiently utilizes resources. In contrast to the linear economy (LE), the CE involves incorporating holistic product life cycle analysis to fit in resource life extension strategies (RLES). But equally, it has to be known that CE is more and beyond the waste management alone, it is about managing the resources to reduce the waste (Upadhayay & Alqassimi, 2019)

Relevant Literature

Cautisanu et al. (2018) incorporated clustering and path analysis to examine the determinants of CE in OECD countries where it stressed the importance of circular strategies in the management of waste created due to the higher consumption as a virtue of economic growth; further it asserted the positive impact of education on GDP per capita and R&D which could foster innovative recycling techniques. Busu and Trica (2019) to assess the sustainability of CE indicators in the economic growth of the EU employed a multi regression model with panel data from 2010 to 2017 and concluded that circular material use rate, recycling rate of municipal waste, resource productivity, and GDP per capital growth to have significant positive impact on the economic growth of the EU.

In an empirical assessment carried by Trica et al. (2019) in EU countries with data from 2007 to 2016, resource productivity, environmental employment, recycling rate, and environmental innovation were found to have strong and positive impact on the economic growth. Grdic et al. (2020) concluded countries with greater GDP have greater municipal waste per capital, those countries using more secondary materials have reduced municipal waste generation and developed countries having higher number of patents in a CE have higher GDP. Likewise, in a study carried out in the European Union (EU) between 2006 to 2016, Robaina et al. (2020) conducted a study across three clusters of RPs (RP growth rate-low, medium and high). While a negative relation was observed between R&D and RP for high cluster countries, the signal was positive for low and medium growth countries.

Methods and Materials

Resource Productivity (RP) which was taken as a proxy variable of CE in this quantitative study is a dependent variable. The Real GDP per capita (GDP), Renewal Energies as the percent of total energy consumption (REN), Research and Development expenses as the percent of GDP (RD) and Municipal Waste Recycled (MWR) were the independent variables. Equation 1 represents the modality of the study where the impact of GDP, REN, RD, and MWR on RP was assessed.

$$RP= f(GDP, REN, RD, MWR) \qquad (1)$$

To employ empirical estimation, a linear transformation on equation (1) was performed yielding equation (2).

$$lnRP_t = a_1 + \beta_1 lnGDP_t + \beta_2 REN_t + \beta_3 RD_t + \beta_4 lnMWR_t + \varepsilon_t \quad (2)$$

Where *ln* represents the natural logarithms of the variables, t and ε_t represents the time and error term respectively and β_1, β_2 β_3, β_4 denote the coefficients associated with the different explanatory variables. Further *β's* represents the long run elasticities to be estimated.

Stationary and Nonstationary Time Series

To test the stationarity of the time series data, Augmented Dickey-Fuller (ADF), Dickey and Fuller (1981), and Phillips and Perron (1988) (P-P) were conducted. P-P noted the limitation of ADF to test the stationarity in small samples and time series data where structural break occurs. Further Zivot-Andrews (2012) (Z-A) unit root test was conducted to analyze the structural break in the time series data.

ARDL Method

The Autoregressive Distributed Lag (ARDL) model is the most general dynamic unrestricted model in econometrics and was developed by Pesaran and Shin (1988) and Pesaran et al. (2001). In ARDL model the dependent variable is expressed by the lag and current value of independent variables and its own lag value (Ghouse et al., 2018). ARDL test is more suitable for small size of data and hence could be choice for this study, since the time for each variable is 47 years only. Nepal and Paija (2019) highlighted the merits of ARDL model with its benefit to remain statistically significant even after the nature of integration orders of variables: I (0), I (1) or both. While the unit root test allows identifying the maximum orders of integration of the time series, ARDL estimates help in confirming the presence or absence of long run and short run equilibrium relationships (Nepal & Paija, 2019). For the purpose of time series analysis, EViews software was employed.

As per Pesaran and Shin (1998) and Pesaran et al. (2001), the ARDL Bounds test for cointegration which consists of long run terms can be stated as:

$$ARDL: \Delta Y_t = \beta_0 + \sum_{i=1}^{p} \beta_i \Delta Y_{t-1} + \sum_{i=0}^{q} \theta_i \Delta X_{t-1} + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-1} + \varepsilon_t \quad (3)$$

After replacing the variables under study in above Equation 3, we get:

$$lnRP_t = b_0 + \sum_{i=1}^{p_1} b_{1i} lnRP_{t-i} + \sum_{i=0}^{q_1} b_{1i} lnGDP_{t-i} + \sum_{i=0}^{q_2} b_{2i} REN_{t-i} + \sum_{i=0}^{q_3} b_{3i} RD_{t-i} + \varepsilon_t \quad (4)$$

Moreover, the possible cointergration in Equation 4 is tested through Bounds test which examins the presenc of long run relationship between the variables in an ARDL model. For Equation 4, the null and alternative hypotheses are as follows:

$H_0 : b_1 = b_2 = b_3 = 0$

$H_1 : b_1 \neq b_2 \neq b_3 \neq 0.$

We reject the H_0 if the test statistic exceeds the respective upper critical value in favor of confirming the existance of long run relationship in the model (the error correction term). In contrast, if test statistics falls below the respective lower critical values, we cannot reject H_0 and conclude that there is no long term adjustment mechanism. But, if the F statistic lies between the upper and lower critical values, the bound test result becomes inclusive.

Once the long run relationship among the vairables was ascertained and cointegration was confirmed in the model, the next step was to develop corresponding error correction model as shown in Equation 5, which could be obtained by reparamatization of Equation 4. Here we investigate the short run dynamics of the respective variables along with the speed of the adjustment towards the long run.

$$\Delta lnRP_t = a_0 + \sum_{i=1}^{p} \gamma_i \Delta lnRP_{t-i} + \sum_{j=0}^{p} \gamma_j \Delta lnGDP_{t-j} + \sum_{k=0}^{p} \gamma_k \Delta REN_{t-k} + \sum_{l=0}^{p} \gamma_l \Delta RD_{t-l} + \lambda ECM_{t-1} + \varepsilon_t \quad (5)$$

In Equation 5, Δ represents the lag operator, ECM_{t-1} indicates error correction term and λ is the coefficient of adjustment. ECM_{t-1} is the lagged oridinary least square (OLS) residuals obtained from running the long run model. The coefficient of ECM_{t-1} is the speed of adjustment to the long run equilibrium. Further, to ensure covergence towards the long run equilibrium, λ has to be less than zero and statistically signficant; otherwise the model is considered unstable or explosive (if λ is positive).

Data

The data for the variables incorporated in this study was extracted from the dataset maintained by National Science Foundation (2019), United Nation- International Resource Panel (2021), U.S. Energy Information Administration (2021), U.S. Environmental Protection Agency (2020), and World Bank (2021).

Real GDP per capita was expressed in an absolute term of dollars, R&D expenses as a percent of GDP, renewal energy as a percent of total energy consumption and RP in U.S. dollar per Kg. Log transformation was taken for GDP per capita (lnGDP) and RP (lnRP) which is a general practice in data analysis that reduces or removes the skewness of the data and helps eliminate heteroscedasticity.

Dependent and Independent Variable

Blomsma and Brennan (2017) asserted RP is an important indicator of CE; calculated as the ratio of GDP of country and its Domestic Material Consumption (DMC) (Haas et al., 2015). Plethora of research across the literatures have kept RP as a proxy variable of CE (Busu and Trica, 2019; Robaina et al., 2020; Trica et al ., 2019), and same practice is continuted in this study.

With an increase in the GDP, the consumption increases and ultimately generates higher waste (Cautisanu et al., 2018); CE could help to bring this waste back as resources for another P&C cycle. The link between CE and economic growth was also emphasized by Bocken et al. (2016); Geissdoerfer et al. (2017); Ghisellini et al. (2016). R&D promotes innovation bringing newer modalities of P&C which could be more efficient and effective. Research and science provide fact-based knowledge that brings technological knowledge required for circular transition (Bassetti, 2020). Investment in R&D is the most to assist complex transition from a LE to a CE. Higher levels of municipal waste symbolizes higher domestic material consumption. This waste could be treated and further given a new life. In CE, waste represents a main resource for P&C. In respect to the renewable energy, a significant positive relation between the use of renewable energy and economic growth exists (Pires and Martinho, 2019).

Table 1
Expected Impact of Independent Variables on Dependent Variable

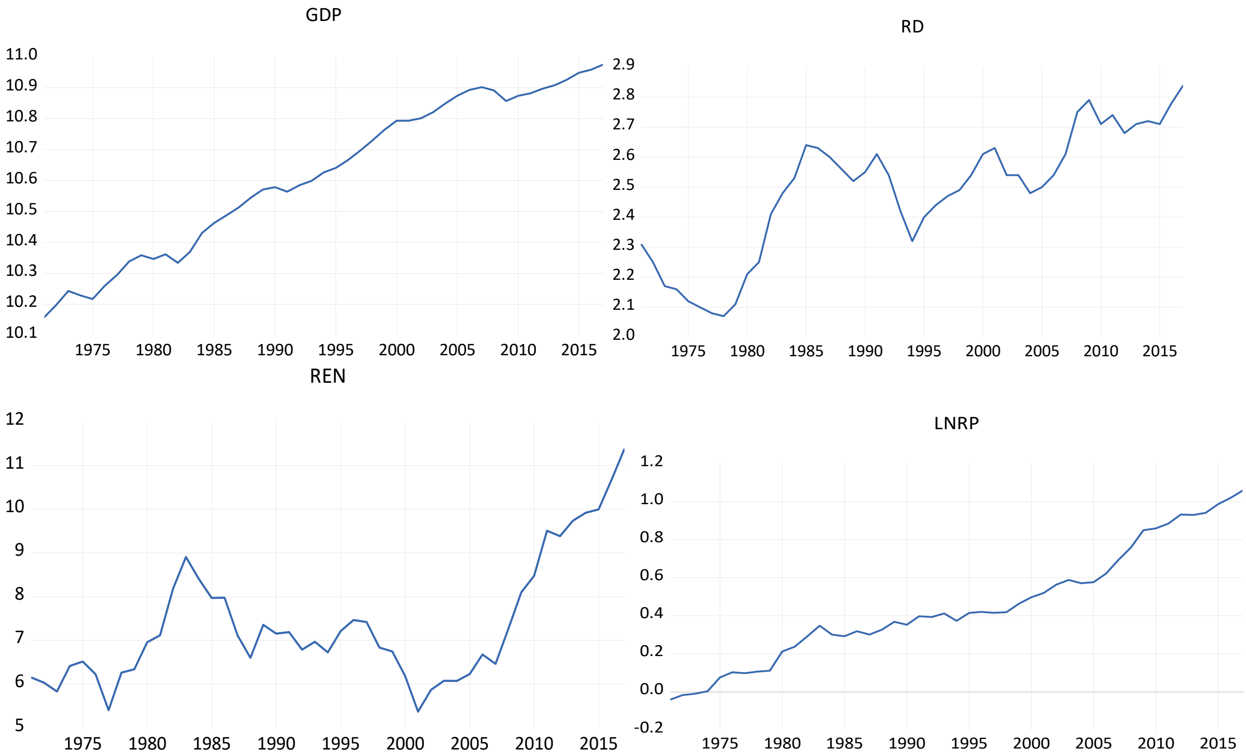
Variables	Type	Expected relation
Resource Productivity	Dependent	Proxy of CE
Gross Domestic Product per capita	Independent	Increases Municipal waste, RP, and CE
Municipal waste recycled	Independent	Increases RP and CE
Total renewable energy consumption	Independent	Increases RP and CE
Resource and Development	Independent	Increases/Decrease RP and CE

Results

Test of Stationarity and Unit Root Tests

All of variables in Figure 1 shows an upward trend; however, RD and REN indicate the existence of structural breaks.

Figure 1
Data Series Used in the Study



ADF and Phillips-Perron tests were employed to assess the stationarity of the time series data. All the varaibles under study were non-stationary at their levels, and stationariy at their first difference.

Table 3
Test of Stationarity

	Augmented Dickey-Fuller Test Statistic		Phillips-Perron Test Statistic	
	Intercept Only	Trend and Intercept	Intercept Only	Trend and Intercept
InGDP	-1.592, (p=0.479)	-1.996, (p=0.588)	-1.792, (p=0.38)	-1.687, (p=0.741)
DInGDP	-5.065, (p=0.000)*	-5.0895, (p=0.001)*	-4.899 (p=0.000)*	-4.924, (p=0.0012)*
InRP	0.666, (p=0.9901)	-1.068, (p=0.923)	0.637, (p=0.989)	-1.999, (p=0.898)
DInRP	-6.151, (p=0.000)*	-6.202, (p=0.000)*	-6.151, (p=0.000)*	-6.202, (p=0.000)*
MWR	-1.890, (p=0.334)	-0.0971, (p=0.993)	-1.768, (p=0.3909)	-0.277, (p=0.989)
DInMWR	-5.492, (p=0.000)*	-5.981, (p=0.000)*	-5.697, (p=0.000)*	-6.089, (p=0.000)*
RD	-1.269 (p=0.636)	-2.807, (p=0.202)	-0.855, (p=0.793)	-2.468, (p=0.342)
DRD	-4.435, (p=0.000)*	-4.393, (p=0.006)*	-4.417, (p=0.001)*	-4.378, (p=0.0058)
REN	0.396, (p=0.981)	-0.424, (p=0.984)	0.008, (p=0.954)	-0.781, (p=0.960)
DREN	-5.610, (p=0.000)*	-5.772, (p=0.000)*	-5.625, (p=0.000)*	-5.785, (p=0.000)*

Note. Critical values reported in this table are based on levels of the variables. Slight changes exist when the first differences of the variables are used in unit root tests. Reported critical values are obtained from EViews 11 output. * represents 1% of significane level.

To identify the point of single most significant structural break in the timeseries data, Zivot-Andrew test was employed further (Table 4). In line with findings from ADF and P-P test, Zivot-Andrew test also reported the same level of integration for all study variables which confirmed that no series was intergated of order 2 or more which justifies the relevenace of ARDL bounds test approach to cointegration.

Table 4
Zivot-Andrews Test

Variables	Z-A test for level			Z-A test for 1st difference		
	t-statistics	Break Year	Outcome	t-statistics	Break Year	Outcome
lnRP	-3.178	1994	Unit Root	-5.871	2008	Stationary
lnGDP	-4.677	2008	Unit Root	-5.917	2008	Stationary
REN	-3.034	2000	Unit Root	-7.547	1984	Stationary
RD	-5.398	1992	Unit Root	-5.642	1986	Stationary

Note. The critical value at 1%, 5%, and 10% is -5.57, -5.08, and -4.82 respectively.

For lnRP, lnGDP, REN and RD the structural break appeared in 2008, 2008, 1984 and 1986. A dummy variable was defined and added to the list of variables under study, Dummies are categorical (binary) variables used in regression models to account for anomalies of structural break in the data. A value of 1 was assigned to Dummy starting from the year 2008 till 2017.

Assessment of Correlation between the Independent Variables

During the process, two of the independent variables, GDP per capita (lnGDP) and Municipal Waste Recycled (MWR) reported a high level of autocorrelation (0.98). With the increase in GDP, the consumption in the economy also increases and so does the creation of waste and ultimately recycling of waste (Cautisanu et al., 2018; Grdic et al., 2020). To get rid of the high level of autocorrelation which may influence the statistical analysis in this test, in further analysis, MWR was dropped from the model and study was carried out only with three independent variables: lnGDP, REN, and RD.

Bounds Test and ARDL Estimations

Table 5 shows the result of the cointegration F test from which we can infer a long-run relationship exists between RP, GDP per capita, RD and REN.

Table 5
Result of Bounds Test of Cointegration

Dependent variables	SIC lag length	F-Statistics	Decision
lnRP (lnGDP, RD, REN, Dummy)	(1,1,0,0,0)	12.36	Co-integration
Critical Value	I (0)	I (1)	
1 Percent significance level	3.29	4.37	
5 Percent significance level	2.56	3.49	
10 Percent significance level	2.2	3.09	

Schwarz information criterion (SIC) model was employed (Robaina et al., 2020); since Akaike information criterion (AIC) often overfits the data and leads to over parameterization (Lin & Tsai, 2016). The calculated F statistics was 12.36 which is greater than the upper limit of critical value at 5 % of significance level, this verified the presence of cointegration among the variables, i.e., RP, GDP, RD, and RE. After confirming the presence of cointegration, long run relationships amongst the variables were studied (Table 6).

Table 6
Long Run Relationship of the Models

Levels Equation Long Run Estimation: Restricted Constant and No Trend				
Variables	Coefficient	Std. Error	t-Statistics	Prob.
LNGDP	0.8543	0.1149	7.4331	0.000
RD	-0.0282	0.1416	-0.1988	0.8435
REN	0.0489	0.0184	2.6531	0.0115
DUMMY	0.1547	0.0656	2.3566	0.0236
C	-8.8097	1.0231	-8.611	0.000
EC= LNRP - (0.8543*LNGDP - 0.0282*RD + 0.0489*REN + 0.1547*DUMMY - 8.8097)				

From Table 6, it is inferred, there exists a significant positive long run relationship of GDP per capita and REN with the RP of the USA. In contrast, no significant long run relationship was observed between RD and RP of the USA. Finally, short run relationships between the variables along will the error correction mechanism was estimated (Table 7).

Table 7
Short Run Relationship and ARDL Error Correction Model

ECM Regressor				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNGDP)	-0.6616	0.226	-2.9276	0.0057
D(RD)	-0.0073	0.0365	-0.2002	0.8424
D(REN)	0.0127	0.0068	1.8624	0.0701
D(DUMMY)	0.0401	0.0221	1.8267	0.0754
CointEq(-1)	-0.2594	0.103	-2.5171	0.0161

Table 7 portrays the short run estimate of the study, we can infer GDP per capita and renewal energy have significant negative and positive impact on RP respectively in the short run while RD has insignificant negative impact on RP in the short run. The error correction term (ECT1-t) was significant with a coefficient of -0.259 which symbolizes that the short run deviations widen the gap between the dependent and independent variables.

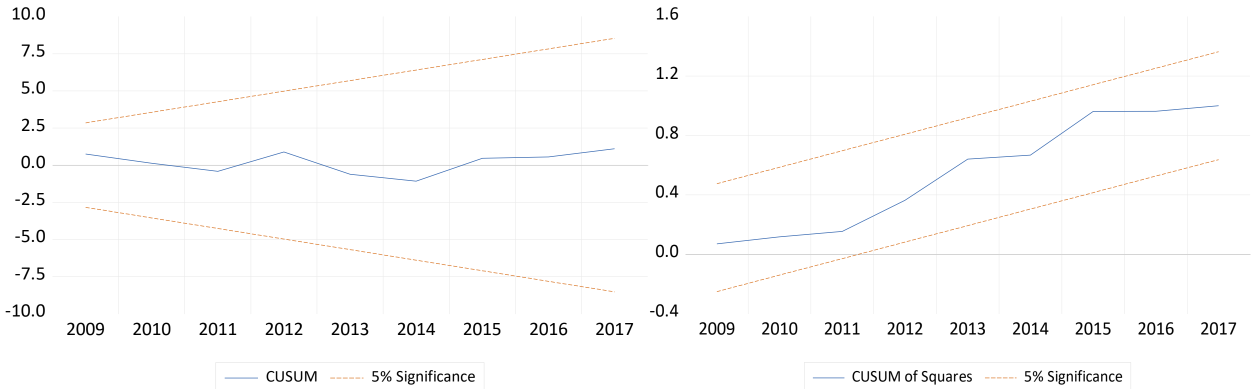
The ARDL model was tested for its stability, fitness and robustness (Table 8). Jarque-Bera (J-B) test of normality, LaGrange Multiplier test for serial correlation, Breusch-Pagan-Godfrey and ARCH test for heteroskedasticity and Ramsey RESET test were within the limit.

Table 8
Diagnostic Test of ARDL Model

Test	F-statistics	p-value
Normality (Jarque-Bera)	0.0054	0.9974
Serial correlation (LM test)	0.7299	0.4887
Ramsey RESET	0.9954	0.3247
ARCH	2.6047	0.1139
Heteroscedasticity (Breusch-Pagan-Godfrey)	0.9061	0.5005
R-Square	44.7%	
Adjusted R-Square	43.53%	

Finally, CUSUM (cumulative sum) and CUSUMQ (cumulative sum of square) test was carried out to test the stability of the model. Figure 2 indicates the model is stable since the residuals are within the critical bounds at the 5% significance level.

Figure 2
CUSUM and CUSUM Square Test



Note. The straight lines represent critical bounds at 5% level of significance.

Discussion

Hypothesis 1: RP is Positively Influenced by GDP per Capita

In the long run, a 1% increase in GDP per capita of the USA will increase resource productivity by almost 0.85%. Whereas, in the short run, a 1% increase in the GDP per capita will reduce the resource productivity of the USA by almost 0.66%. An increase in GDP per capita represents the expansion of a country's economy which provides numerous opportunities to practice and employ circular strategies, which requires changing the existing P&C patterns. The short-run variations in our existing economic model, which as per Circular Economy (2020) is only 9% circular, could exert pressure on the resources (technical as well as non-technical) which are accustomed to thriving in the linear model of P&C. However, at the same time, it should not be forgotten that CE is a long-term process (Kirchherr et al., 2017; van Buren et al., 2016).

Over time, with an increase in the circular expertise, enhanced know-how about CE, greater diffusion of CE in the industries, strong formation of alliance amongst the firms in the industry to share the circular knowledge, symbiosis, and cross-pollination of CE-related skills across the industries, in the long run, all the intermediaries would start to adapt themselves with circular P&C, and the positive benefits from the CE could be observed in the economy.

Hypothesis 2: RP is Positively Influenced by Renewable Energy Consumption

In the long run, a 1% increase in the REN will increase the RP of the USA by almost 0.05 %. Similarly, in the short run, a 1% increase in the consumption of renewal energy would increase the resource productivity of the USA by 0.013%. With the consumption of renewable energies, the RP of the USA exhibited a significant positive relationship both in the short run and in the long run at 10% and 5% of significance respectively. Investment in renewable energies has a multiplier effect throughout the economy. It reduces emission and improves health, benefits society by avoiding costly illness and job creation, boost the economy by lowering energy costs and helps in diversifying the fuel mix, and reduces the dependency on hydrocarbons (EPA, 2018).

Hypothesis 3: RP is Positively Influenced by the R&D Expenses

In both the long run and the short run, there exists no significant relationship between the Research and Development and resource productivity of the USA. While, in general, it is assumed that the impact of R&D on RP is to be positive and significant, research by Hammar and Belarbi (2021) concluded that the effect of R&D expenditures and innovation on productivity is mixed, i.e., positive, negative and no impact based on the level of the economy.

While the researcher of this study expected a significant and positive relationship between the R&D and RP of the USA, the finding came opposite. This contradictory signal may be because R&D investments might have been in sectors that do not help improve productivity (Robaina et al., 2020). Griliches (1979) pointed out the importance of stock of R&D knowledge and cumulative R&D effort made to date. These could create a spillover effect of R&D achievements, i.e., make the R&D findings quickly diffused in the economy. However, since CE is a new and emerging concept, there is a lack of expertise related to circular innovation, low awareness of CE, a lack of R&D focusing on CE, and a gap in R&D commitment and its actual realization. All of these factors in the USA have abstained the USA from forming the required CE-related pool of knowledge and expertise, which could have negatively impacted the RP.

The error correction term in this estimation as calculated in Equation 7 indicated the causal relationship of the explanatory variables with the dependent variable. The negative sign infers the convergence from short run to long run and could be concluded that approximately 26% of the disequilibrium due to shocks to the system is corrected within one year, and adjustment to the long run path is completed in less than four years.

Conclusion

The study demonstrated there exist a long run as well as short run relation between the GDP per capita and renewable energy consumption to the RP of the USA. However, no relationship existed between R&D and RP of the USA. While there was a negative relation between the GDP per capita and RP in the short run, the relationship would turn positive with higher unit of GDP generated per unit of resource consumed; this could be attributed to the implementation of circular strategies which would focus on RLES.

The findings of this study are in line with the study by Robaina et al. (2020), amongst the EU countries, concluded a positive relationship between renewable energy consumption with countries depicting high growth rates in RP. Similarly, a negative relation between R&D expenditure and RP was obtained in EU countries (Robaina et al., 2020), which is consistent with this study, except the relation was insignificant between R&D and RP in this study. Finally, consistent with this study's findings, Busu and Trica (2019) and Trica et al. (2019) had inferred a positive relationship between the GDP per capita and RP in their study carried out in the EU. The same rule of thumb might not be applicable in determining the factors that would impact the transition from the LE to the CE mode of P&C; Upadhayay and Alqassimi (2020) defined the Good Point for Transition (GPT) which depends on the stock of CE related skills, expertise, and resources.

For the effective and efficient transition to CE in the USA, policies and programs should be in place to increase awareness about CE through the initiation of CE and sustainability related courses and trainings in schools, universities and corporations; there should be sufficient allocation of fund for R&D involving CE related experimentations and innovations; here agencies like U.S. Environmental Protection Agency, U.S. Energy Information Administration, U.S. National Science Foundation, World Bank, and International Monetary Fund could play pivotal role; a creation of regional blocks and special interest committee to foster adoption of CE in national and global arena is a mandate which would dissipate CE related toolkits, data, and measures, and finally, promoting the consumption of renewable energies through various financial and non-financial incentive would support the transition to CE for the sustainable future in the USA.

References

Alhawari, O., Awan, U., Bhutta, M. S., & Ülkü, M. (2021). Insights from circular economy literature: A review of extant definitions and unravelling paths to future research. *Sustainability, 13*(2), 859, https://doi.org/10.3390/su13020859.

Bassetti, F. (2020, Feburary 7). *Science and research can close the loop, for a genuinely circular economy*. https://www.climateforesight.eu/jobs-growth/science-research-circular-economy/.

Blomsma, F., & Brennan, G. (2017). The emergence of circular economy. A new framing around prolonging resource productivity. *Journal of Industrial Ecology, 21*(3), 603-614. https://doi.org/10.1111/jiec.12603.

Bocken, N., Miller, K., & Evans, S. (2016). Assessing the environmental impact of new Circular business models. In J. Jonker, & N. R. Faber (Eds.), *The proceedings of the First International Conference on "New Business Models": Exploring a changing view on organizing value creation* (pp. 17-18). Toulouse Business School.

Boulding, K. E. (1966). *The economics of coming spaceship earth*. John Hopkins University Press.

Brown, P. G. (2004). An Economics for spaceship earth. A time for witness- A time for service. *Quaker Eco-Bulletin. 4*(2).

Busu, M., & Trica, C. L. (2019). Sustainability of circular economy indicators and their impact on economic growth of the European Union. *Sustainability,11*(19), 5481, https://doi.org/10.3390/su11195481.

Cautisanu, C., Asandului, L., Borza, M., & Turturean, C. (2018). Quantitative approach to circular economy in the OCED countries. *Afiteatru Economic, 20*(48), 262-277. https://doi.org/10.24818/EA/2018/48/262.

Circular Economy. (2020). *The circularity gap report 2020*. https://www.circularity-gap.world/2020.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica, 49*(4), 1057-1072. https://doi.org/10.2307/1912517.

EPA. (2018). Quantifying the multiple benefits of energy efficiency and renewable energy. https://www.epa.gov/sites/default/files/2018-07/documents/epa_slb_multiple_benefits_508.pdf.

Geissdoerfer, M., Savaget, P., Bocken, N. M., & Hultink, E. J. (2017). The circular economy – A new sustainability paradigm? *Journal of Cleaner Production, 143*, 757-768. https://doi.org/10.1016/j.jclepro.2016.12.048.

Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: the expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner Production,114*, 11-32. https://doi.org/10.1016/j.jclepro.2015.09.007.

Ghouse, G., Khan, S. A., & Rehman, A. U. (2018). ARDL model as a remedy for spurious regression: Problems, performance and prospectus. *MPRA*, Paper No. 83973, https://mpra.ub.uni-muenchen.de/83973/.

Grdic, Z. S., Nizic, M. K., & Rudan, E. (2020). Circular economy concept in the concept in the context of economic development in EU countries. *Sustainability, 12*(7), 3060 https://doi.org/10.3390/su12073060.

Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics, 10*(1), 92-116. https://doi.org/10.2307/3003321.

Hammar, N., & Belarbi, Y. (2021). R&D, innovation and productivity relationships: Evidence from threshold panel model. *International Journal of Innovation Studies, 5*(3), 113-126. https://doi.org/10.1016/j.ijis.2021.06.002

Haas, W., Krausmann, F., Wiedenhofer, D., & Heinz, M. (2015). How circular is the global economy? An assessment of material flows, waste production, and recycling in the European Union and the World in 2005. *Journal of Industrial Ecology, 19*(5), 765-777. https://doi.org/10.1111/jiec.12244.

Hickel, J. (2018, May 15). *The great challenge of the 21st century is learning to consume less. This is how we can do it*. WEF. https://www.weforum.org/agenda/2018/05/our-future-depends-on-consuming-less-for-a-better-world/

Kirchherr, J., Reike, D., & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation & Recycling, 127*, 221-232.

Lin, T. H., & Tsai, M.-H. (2016). Model selection criteria for dual-inflated data. *Journal of Statistical Computation and Simulation, 86*(13), 2663-2672. https://doi.org/10.1080/00949655.2015.1118102.

Mosbergen, D. (2016, August 3). *Our consumption of earth's natural resources has more than tripled in 40 years*. Huffpost. https://www.huffpost.com/entry/natural-resource-use-tripled_n_57a05c3ae4b0693164c273a8

National Science Foundation. (2019). National Patterns of R&D Resources 2017-2018. https://ncses.nsf.gov/pubs/nsf20307.

National Center for Science and Engineering Statistics 2019, NSF 20-307.

Nepal, R., & Paija, N. (2019). Energy security, electricity, population and economic growth: The case of a developing South Asian resource-rich economy. *Energy Policy,132*, 771-181. https://doi.org/10.1016/j.enpol.2019.05.054.

Pesaran, H. M., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics, 16*(3), 289-326. https://doi.org/10.1002/jae.616.

Pesaran, M. H., & Shin, Y. (1998). An autoregressive distributed lag modelling approach to cointegration analysis. *Econometric Society Monographs, 31*, 727-731.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika,75(*2), 335-436.

Pires, A., & Martinho, G. (2019). Waste hierarchy index for circular economy in waste management. *Waste Management, 95*, 298-305. https://doi.org/10.1016/j.wasman.2019.06.014.

Robaina, M., Villar, J., & Pereira, E. T. (2020). The determinants for a circular economy in Europe. *Environmental Science and Pollution Research, 27*, 12566-12578. https://doi.org/10.1007/s11356-020-07847-9.

Smith, A. (1972, September). The last days of cowboy capitalism. The Atlantic Monthly, 230. https://search.proquest.com/docview/204115216?accountid=158986.

Trica, C. L., Banacu, C. S., & Busu, M. (2019). Environmental factors and sustainability of the circular economy model at the European Union level. *Sustainability, 11*(4) 1114, https://doi.org/10.3390/su11041114.

U.S. Energy Information Administration. (2021). *Renewable energy production and consumption by source*. EIA. https://www.eia.gov/totalenergy/data/browser/index.php?tbl=T10.01#/?f=A&start=1958&end=2019&charted=6-7-8-9-14

U.S. Environmental Protection Agency. (2020). *Sustainable materials management (SMM) - Materials and waste management in the United States key facts and figures*. US EPA. https://edg.epa.gov/metadata/catalog/search/resource/details.page?uuid=C9310A59-16D2-4002-B36B-2B0A1C637D4E

United Nation- International Resource Panel. (2021). *Global material flow database.* Resource panel. https://www.resourcepanel.org/global-material-flows-database

United Nations. (2019). *Global Resources Outlook. UN environment. https://wedocs.unep.org/handle/20.500.11822/27518*

Upadhayay, S., & Alqassimi, O. (2019). A survey on understanding the perception and awareness towards a circular economy. A comparative study between Nepal and the USA. *Westcliff International Journal of Applied Research, 3*(1), 37-46. https://doi.org/10.47670/wuwijar201931SUOA.

Upadhayay, S., & Alqassimi, O. (2020). A study on assessing a business viability for transition to a circular economy. *Westcliff International Journal of Applied Reseearch,4*(1), 72-77. https://doi.org/10.47670/wuwijar202041SUOA.

Van Buren, N., Demmers, M., van der Heijden, R., & Witlox, F. (2016*). Towards a circular economy: The role of Dutch logistics industries and governments. Sustainability, 8*(7), 647. https://doi.org/10.3390/su8070647

World Bank. (2021). *World Development Indicators.* https://databank.worldbank.org/country/USA/556d8fa6/Popular_countries#

Zivot, E., & Andrews, D. K. (2012). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business & Economic Statistics, 20*(1), 25-44. https://doi.org/10.1198/073500102753410372.

Towards Understanding the Consumer Behavior of Mobile Banking Applications for Management Decision Makers

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Abstract

The rapid growth of mobile applications in the banking sector has been increasing due to the ease of use and saving the time of users. However, the fierce competition between banks draws attention to the factors that increase the use of banking mobile applications to maintain the level of satisfaction of the customers of each bank. One of the crucial aspects that decision-makers need to understand is the consumer behavior of mobile banking applications. Therefore, this research paper aims to present a comprehensive exploration of mobile banking adoption by examining the interplay of cultural dynamics, usability, cross-cultural comparisons, economic factors, and the significance of longitudinal insights. It elucidates how cultural norms and societal expectations impact adoption, emphasizing regional variations. The study also dissects mobile banking app interfaces to enhance user-friendliness, tailoring them to diverse user preferences. Cross-cultural comparisons shed light on the interplay between culture, economics, and regulations. It scrutinizes economic factors, considering income levels and financial literacy while emphasizing the importance of longitudinal studies for tracking evolving adoption patterns. This research not only advances our knowledge of mobile banking adoption but also offers practical insights for banks, policymakers, and service providers as they navigate the rapidly evolving mobile banking landscape in an increasingly digital world.

Keywords: Mobile banking, consumer behavior, banking decision making

Introduction

The landscape of the banking industry has been significantly reshaped by the emergence of disruptive mobile innovations, leading to a profound impact on traditional retail banks. These incumbents are encountering intense competition emanating from agile and tech-savvy entrants that have harnessed the power of mobile technology (Al Tarawneh et al., 2023). As a result, conventional banks are compelled to undertake strategic initiatives aimed at fortifying their market positions. One prominent response has been the heightened investment in mobile channels, as these establishments recognize the imperative of adapting to evolving consumer preferences and habits. The shift towards mobile-centric services is not merely an option for traditional banks; rather, it has become an essential avenue for them to uphold and enhance their competitive edge in the modern financial services landscape (Ho et al., 2020)

Attending to consumer behavior within the realm of mobile applications is of paramount importance for decision-makers. Understanding how users interact with these applications provides critical insights into preferences, pain points, and usage patterns. This knowledge aids in refining app design, optimizing user experiences, and tailoring marketing strategies. Informed decisions rooted in consumer behavior data lead to increased customer satisfaction, higher retention rates, and improved app performance. Moreover, aligning app features with user expectations enhances competitiveness in the market. Hence, prioritizing consumer behavior analysis empowers decision-makers to proactively address user needs, driving overall success in the dynamic landscape of mobile applications (Shahid et al., 2022)

There is a noticeable deficiency in the existing literature concerning thorough examinations of consumer behavior in mobile banking. This gap necessitates research that collects specific studies from diverse countries to comprehensively address five key aspects: factors influencing mobile banking adoption, cultural dynamics and adoption patterns, usability and interface quality, trust in mobile banking adoption, finally usability and user experience.

By addressing this gap and emphasizing the importance of comprehending consumer behavior in mobile banking, valuable insights will be provided to decision-makers. These insights will enable them to refine strategies and make informed decisions aimed at enhancing mobile banking services and consequently augmenting customer retention rates.

The aim of this study, as a review paper, is to establish a set of specific inclusion criteria crucial for defining the scope of this research. These criteria, outlined in the table below, encompass elements such as the search keywords used, the language of publications, publication dates, the countries where studies were conducted, and the subject field. Each of these criteria plays a vital role in shaping the methodology and context of this study, ensuring that the research is focused and relevant. By adhering to these inclusion criteria, this paper aims to maintain accuracy and integrity in its investigative approach.

The following Table 1 summary explains how the research was conducted, including what factors led to choosing which information to include or exclude. This helps clarify how the research participants were chosen and why certain information was considered while other aspects were not.

Table 1
Research Methodology for Selecting Papers

Inclusion Criteria	Description
Search String:	“Consumer Behavior” AND “Mobile Banking”
Language	English
Publishing date	After 2018
Country of conducting study	Select different studies form distinctive countries as possible to enrich the study
Subject Field	Consumer behavior from business perspective
Source of Papers	ProQuest digital Library
Journals	IEEE, Elsevier, ScienceDirect
Excluded Criteria	
Absence of clear methodology	The absence of having clear methodology to follow inside the research
Absence of business values for banking Decision makers	The papers who failed to provide recommendations to business decision makers have been excluded
Type of research	Surveys are excluded, in order to have authentic systematic review without affecting this study with prior surveys.
Number of papers	10 papers will be included in this study to for focusing reason.

In the upcoming paragraph, a detailed explanation will be provided concerning the selection and examination of ten specific papers. This discussion aims to offer insights into the rationale behind the choice of these papers and the subsequent analysis they underwent. By elaborating on the selection process and the significance of these chosen papers, a comprehensive understanding of their relevance to the study will be established.

Drawing upon the strengths identified within these selected studies, this research centered its attention on specific focal points. Primarily, this paper endeavored to provide answers to the following research inquiries:

1. Factors Influencing Mobile Banking Adoption: What are the key factors influencing mobile banking adoption in different cultural contexts such as India, Australia, Lebanon, the UK, the USA, Egypt, Brazil, and China?
2. Cultural Dynamics and Adoption Patterns: How do cultural factors impact the adoption intentions and patterns of mobile banking among diverse customer segments, with a focus on India and the countries of Lebanon, the UK, the USA, and Egypt?
3. Usability and Interface Quality: What essential elements shape user decisions and contribute to the development of user-friendly interfaces in the context of mobile banking applications, and how do these factors vary between different regions such as Australia and Saudi Arabia?
4. Trust in Mobile Banking Adoption: How do privacy and security concerns influence user engagement and trust in the adoption of mobile banking, particularly in countries like Brazil and China?
5. Usability and User Experience: What role does the seamless and intuitive user experience play in the adoption of mobile banking applications, and how does it differ in terms of usability factors between countries like Malaysia and Australia?

These research questions reflect the strengths of the selective studies by addressing the gaps in the literature and seeking to provide a more in-depth, nuanced understanding of mobile banking adoption and user behavior in various cultural, economic, and regulatory contexts. Answering these questions can contribute valuable insights to inform strategies for banks, policymakers, and service providers in the dynamic mobile banking landscape.

Discussion

Examining consumer behavior across various countries necessitates a comprehensive approach that considers multiple dimensions. Decision-makers need to address several aspects to enhance the effectiveness of mobile banking applications. The intricacies of consumer behavior, especially when studied in diverse cultural contexts, highlight the importance of a nuanced strategy. This involves understanding the interplay of socio-cultural, economic, technological, and psychological factors that influence how consumers use mobile banking. Improving the usage of mobile banking applications requires incorporating insights from this in-depth analysis of global consumer behavior trends.

Exploring the landscape of mobile banking adoption across the globe involves a complex tapestry of factors. This review amalgamates a spectrum of studies examining adoption drivers, cultural impacts, user interface intricacies, trust dynamics, and usability facets. By interweaving these diverse elements, the review aims to paint a comprehensive picture, shedding light on the intricate web of influences that delineate the adoption trends of mobile banking applications on a global scale.

Kumar et al. (2020) and Shankar et al. (2020) contribute to this understanding by exploring factors influencing mobile banking adoption in India and Australia, respectively. Kumar et al. extend the Technology Acceptance Model (TAM) to grasp adoption intentions among Indian customers, focusing on effective marketing strategies. Shankar et al. employ the Elaboration Likelihood Model to assess the impact of online word-of-mouth and trust in India, acknowledging nuanced differences in consumer behavior. Both studies collectively underscore the importance of trust and user involvement in mobile banking adoption.

Merhi et al. (2020) and Hassan & Wood (2020) delve into the influence of cultural factors on mobile banking adoption, examining different national settings such as Lebanon, the UK, the USA, and Egypt. Merhi et al. emphasize the role of gender and age in Lebanon and the UK, while Hassan & Wood identify the collective nature of Egyptian society's influence on adoption. Both studies highlight the complex interplay between cultural norms and adoption patterns, suggesting a need for more detailed exploration of the cultural dynamics shaping user behaviors in these regions.

Turning to the user elements and interface quality of mobile banking applications, Van Deventer (2022) and Alhejji et al. (2022) contribute with some insights. Van Deventer identifies essential elements, such as attitude, trust, and structural assurances that shape user decisions, emphasizing the importance of a user-friendly interface and support. Alhejji et al. present a benchmark comparison of mobile applications in Saudi Arabia, recognizing challenges in user interface design and customer support. Both studies concur on the significance of user-friendly interfaces and reliable customer support but suggest a need for more in-depth analysis of these issues.

Hochin & Jaroenwanit (2023) and Gbongli et al. (2020) focus on trust as a critical element in mobile banking adoption, but within different national contexts, Brazil and China, respectively. Hochin & Jaroenwanit underscore privacy and security concerns as pivotal determinants of sustained engagement in the Brazilian context. Gbongli et al. examine trust and perceived risk in technology adoption within the Chinese context. Both studies highlight the importance of trust but differ in their contextual approaches and methodological foundations.

Lastly, Al Tarawneh et al. (2023) and Zubaydi & Gide (2018) explore the usability and user experience of mobile banking applications. Al Tarawneh et al. underline the significance of seamless and intuitive user experiences in service delivery, especially for Generation Y in Malaysia. Zubaydi & Gide conduct a comparative analysis in Australia, focusing on factors like purchase-related inconveniences and transactional efficacy. Both studies offer valuable insights into usability, considering distinct contexts and acknowledging potential regional disparities.

Table 2
Highlighted Addressed Themes in this Study of Selected Papers

Theme	Studies
Factors Influencing Mobile Banking Adoption	Kumar et al. (2020): Investigating factors influencing mobile banking adoption in India. Shankar et al. (2020): Examining factors affecting mobile banking adoption in Australia. Hochin & Jaroenwanit (2023): Investigating trust in mobile banking adoption in Brazil. Gbongli et al. (2020): Exploring trust and perceived risk in mobile banking adoption in China.
Cultural Dynamics and Adoption Patterns	Kumar et al. (2020): Examining adoption intentions among Indian customers. Hassan & Wood (2020): Emphasizing the role of cultural factors in Lebanon, the UK, the USA, and Egypt.
Usability and Interface Quality	Van Deventer (2022): Identifying essential elements shaping user decisions and user-friendly interfaces. Alhejji et al. (2022): Presenting a benchmark comparison of mobile applications in Saudi Arabia and addressing user interface design. Al Tarawneh et al. (2023): Highlighting usability and user experience in mobile banking applications in Malaysia. Zubaydi & Gide (2018): Comparing usability factors in banking and gaming applications in Australia.
Trust in Mobile Banking Adoption	Hochin & Jaroenwanit (2023): Highlighting privacy and security concerns as determinants of user engagement in Brazil. Gbongli et al. (2020): Examining trust and perceived risk in technology adoption in China.
Usability and User Experience	Al Tarawneh et al. (2023) - Underscoring the importance of seamless and intuitive user experiences in Malaysia. Zubaydi & Gide (2018) - Conducting a comparative analysis of usability factors in Australia.

Finally, Table 3 presents a comprehensive summary of the findings, organized according to various key aspects. These include the method of data collection and the underpinning framework whether derived from established theories or developed as an independent conceptual model. Additionally, the table highlights the volume of records scrutinized within each study, offering insight into the scale of analysis. Lastly, the geographical context is also provided, denoting the country in which each respective study was conducted, thereby enhancing the contextual understanding of the research.

Table 3

Summary of the Reviewed Papers that Illustrated Data Collection Method, Consumer Behavior Framework Number of Records of Users, and Country of the Study.

Paper	Data Collection Methodology	Consumer Behavior Framework of the study	Number of studied Users	Country of the Study
Kumar et al (2020)	Survey	Extended Traditional Acceptance Model (ETAM)	302	India
Van Deventer (2022)	Survey	Conceptual Model Six-Factor Structure	334	South Africa
Merhi et al. (2020)	Online Survey	Extension of UTAUT2 Framework	897	England Lebanon
Shankar et al. (2020)	Survey	New Conceptual Model	1153	India
Al Tarawneh et al. (2023)	Survey	UTAUT	504	Malaysia
Alhejji et al. (2022)	Observation, Data-Driven	Conceptual Model	8396	Saudi Arabia
Gbongli et al. (2020)	Online Survey	Conceptual Model	612	China
Hassan & Wood (2020)	Survey	Technology Acceptance Model (TAM)	660	USA Egypt
Hochin & Jaroenwanit (2023)	Survey	UTAUT	400	Brazil
Zubaydi & Gide, (2018)	Online Survey	Quantitative Analysis	202	Australia

Table 3 encompasses diverse research methodologies in studies on mobile banking adoption across several countries. Kumar et al. (2020) utilized a survey with the Extended Traditional Acceptance Model (ETAM) in India, while Merhi et al. (2020) conducted an online survey in England, extending the UTAUT2 framework. Alhejji et al. (2022) employed a conceptual model with observations from an online database in Saudi Arabia, and Gbongli et al. (2020) used an online survey with a conceptual model in China. Zubaydi & Gide (2018) adopted an online survey with quantitative analysis in Australia. These varied methodologies underscore the global nature of mobile banking adoption research, emphasizing the necessity for nuanced insights tailored to diverse cultural contexts.

Recommendations

In forthcoming research endeavors, it is imperative to advance the current comprehension of mobile banking adoption. This necessitates an in-depth exploration of cross-cultural intricacies, a nuanced refinement of usability analyses, and a comprehensive examination of the multifaceted dynamics governing trust. Comparative studies spanning diverse geographic regions coupled with granular scrutiny of cultural influences will serve to enrich our understanding, enabling the formulation of precise strategies and the augmentation of user experiences within the dynamic landscape of mobile banking services.

Conclusion

The synthesis of findings from diverse studies on mobile banking adoption underscores the intricate tapestry of factors influencing user behavior. Cultural dynamics, usability considerations, and trust emerge as pivotal determinants shaping adoption patterns across varied geographical contexts. This nuanced understanding is of paramount importance for decision-makers in the banking sector. Acknowledging these multifaceted influences equips them to formulate targeted strategies that resonate with diverse user preferences and cultural intricacies. In an evolving landscape, such insights are imperative for informed decision-making, ensuring the effective implementation of mobile banking services and the optimization of user experiences.

References

Al Tarawneh, M. A., Nguyen, T. P. L., Yong, D. G. F., & Dorasamy, M. A. (2023, May 18). Determinant of m-banking usage and adoption among millennials. *Sustainability*, *15*(10), 8216. https://doi.org/10.3390/su15108216

Alhejji, S., Albesher, A., Wahsheh, H., & Albarrak, A. (2022, November 29). Evaluating and comparing the usability of mobile banking applications in Saudi Arabia. *Information, 13*(12), 559. https://doi.org/10.3390/info13120559

Carlin, B., Olafsson, A., & Pagel, M. (2022, June 29). Mobile apps and financial decision making. *Review of Finance*, *27*(3), 977–996. https://doi.org/10.1093/rof/rfac040

Gbongli, K., Xu, Y., Amedjonekou, K. M., & Kovács, L. (2020, February 11). Evaluation and classification of mobile financial services sustainability using structural equation modeling and multiple criteria decision-making methods. *Sustainability, 12*(4), 1288. https://doi.org/10.3390/su12041288

Hassan, H. E., & Wood, V. R. (2020). Does country culture influence consumers' perceptions toward mobile banking? A comparison between Egypt and the United States. *Telematics and Informatics*, *46*, 101312. https://doi.org/10.1016/j.tele.2019.101312

Ho, J. C., Wu, C. G., Lee, C. S., & Pham, T. T. T. (2020, November). Factors affecting the behavioral intention to adopt mobile banking: *An international comparison. Technology in Society, 63, 101360.* https://doi.org/10.1016/j.techsoc.2020.101360

Hochin, R., & Jaroenwanit, P. (2023). Factors affecting trust and intention to continue using mobile banking: A case of a-mobile application. *Varazdin Development and Entrepreneurship Agency (VADEA).*

Kumar, A., Dhingra, S., Batra, V., & Purohit, H. (2020, June). A framework of mobile banking adoption in India. *Journal of Open Innovation: Technology, Market, and Complexity, 6(2), 40*. https://doi.org/10.3390/joitmc6020040

Merhi, M., Hone, K., Tarhini, A., & Ameen, N. (2020, August 24). An empirical examination of the moderating role of age and gender in consumer mobile banking use: a cross-national, quantitative study. *Journal of Enterprise Information Management, 34*(4), 1144–1168. https://doi.org/10.1108/jeim-03-2020-0092

Shahid, S., Islam, J. U., Malik, S., & Hasan, U. (2022, March). Examining consumer experience in using m-banking apps: A study of its antecedents and outcomes. *Journal of Retailing and Consumer Services, 65,* 102870. https://doi.org/10.1016/j.jretconser.2021.102870

Shankar, A., Jebarajakirthy, C., & Ashaduzzaman, M. (2020, January). How do electronic word of mouth practices contribute to mobile banking adoption? Journal of Retailing and Consumer Services, *52*, 101920. https://doi.org/10.1016/j.jretconser.2019.101920

Van Deventer, M. (2022). Mobile banking behavioural usage intention among South African generation Y consumers. *Social*

Science Research Network. https://doi.org/10.2139/ssrn.4214231

Zubaydi, M., Gide, E., & Guo, W. (2018). A study of consumer spending behaviour in the Australian mobile application market. Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE). Nadi, Fiji, 2018, pp. 259-264, https://doi.org/10.1109/apwconcse.2018.00049