The Study on the Impact of Business Artificial Intelligence Innovation on Fair Value Investments in the United States

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The purpose of the study is to offer valuable insights into how artificial intelligence is revolutionizing investment practices, and the impact of this transformation on investors, as well as the wider financial market scenario in the United States. The study investigated how the use of advanced AI technologies in business settings affects the valuation and fairness of investments in the United States. The goal of this research is to provide insights into how AI can influence financial decision-making and improve investment outcomes. The study findings suggest that AI possesses the potential to influence investor behavior, as AI-powered analytics and robot-advisors continue to gain prominence in guiding investment decisions. The increasing integration of AI in business practices raises ethical and regulatory concerns that impact public perception and the regulatory landscape, thereby affecting investment values. AI-based tools can process vast amounts of data accurately and quickly, enabling identification of investment opportunities, risks, and trends more efficiently than traditional methods. This, in turn, could foster better investment decisions and potentially higher returns.

Keywords: artificial intelligence, business innovation, fair value investment, business behaviors, financial market, analytics

INTRODUCTION

The research discussed involves a comprehensive examination of the impact of cutting-edge artificial intelligence (AI) innovations on the fair value of investments in the United States. Most organizations aim to be innovative and do not understand how to define AI innovation (McGowan, 2016). Business managers pursue ways to improve profits and efficiency by integrating AI innovations without preparation and information, eventually affecting productivity and revenue (Kim & Min, 2015). According to Blair (2015), AI innovation can potentially improve a business's competitive benefits. The social problem is that management AI innovation being implemented within an organization is limited even though it has received attention over the past few years (Birkinshaw et al., 2008).

Considering new, upcoming technology is not always complimented when a new idea arrives. New technologies that are introduced carry a risk to consumer acceptance of AI innovative technologies (Adner, 2006, p. 1), and customers must also adopt the ideas of AI innovation. Fifty-six percent of IT leaders believe that there is not a definite meaning on what AI innovation is but feel AI innovation is a necessity in businesses (McGowan, 2016). The specific management problem is the limited understanding of how AI innovation management relates to the organization's performance (Luncheon, A. & Kasztelnik, K., 2021). Suppose C-level executives do not understand management AI innovation and how it affects their organization's performance. In that case, an organization may lose money in the wrong investments causing a decline in the organization's performance. Another aspect this research study can help understand is that if C-level executives understand the organization's innovative needs and wants, their employees can expand their business profits.

THEORETICAL FOUNDATION

In this section, we discuss the theories that my research study is based upon. we searched several different theories regarding technology, user type, location, behaviors, and adoption time. The theory of planned behavior and task technology fit were considered but were not chosen based on this research study. The theories reviewed exhaustively are the theory of economic development, AI innovation diffusion theory, and the UTAUT and UTAUT2, which were used to form this study's research questions. Morris's (2013) theory of AI innovation on a continuum from continuous incremental, business model AI innovation warfare, and discontinuous disruptive AI innovation. Schumpeter's economic development theory defined AI innovation as a change in the current production system and is introduced to make profits and reduce costs (Schumpeter, 2003). This section also discusses the technology acceptance model and AI innovation resistance theory in depth.

INNOVATION DIFFUSION THEORY

AI Innovation diffusion theory, also known as the diffusion of AI innovation, was introduced in 1962 and was later rectified by Rogers (1995). Rogers defined the diffusion of AI innovation as "an idea, practice, or object that is perceived as new by an individual or other unit of adoption (Wani & Ali, 2015)." Diffusion is also the method of an innovative idea that is conveyed through certain channels over time (Rogers, 1995). In a seminal book, Rogers (1995) discussed four main elements of diffusion of AI innovation as: (a) the AI innovation, (b) communication channels, (c) time, and (d) the social system.

The AI innovation itself such as technological AI innovation, the information and uncertainty of the innovative hardware or software aspect have characteristics of either an advantage, compatibility, complexity, trialability, observability, and/or a re-invention which can be adopted or not (Rogers, 1995, pp. 14–16). Communication channels are the different ways to communicate specific AI innovations. Rogers (1995) described *mass media channels* as the quickest ways to get the word out (newspapers, television, radio, etc.) and *interpersonal channels* such as face-to-face communications (p. 18).

The third and fourth elements of diffusion is time and the social system. Time within the diffusion process is the amount of time the AI innovation is accepted or rejected. Suppose the AI innovation is accepted or adopted. In that case, there is a rate of adoption into the social system which is measured by both the number of members that accept the AI innovation and how long the adoption takes (Rogers, 1995, p. 20).

UTAUT AND UTAUT2

UTAUT is a framework developed by Venkatesh et al. (2003) to predict the acceptance of technology within organizational settings (p. 426). UTAUT is classified into four different types that influence human behaviors with the intentions of using technology: (a) new exogenous, (b) new endogenous, (c) new moderating, and (d) new outcome mechanisms (Venkatesh et al., 2016). An extension of UTAUT is known as UTAUT2 which is still in its infancy (Tamilmani et al., 2021). The main difference between UTAUT and UTAUT2 is that UTAUT2 utilizes three different constructs: (a) hedonic motivation, (b) price value, and (c) habit (Chang, 2012). The research conducted between UTAUT and UTAUT2 shows that the better outcomes of "behavioral intentions from (56 percent to 74 percent) and technology usage (40 percent to 52 percent)" (Chang, 2012, p.107); therefore, UTAUT2 is one of the theoretical foundations that was used for this quantitative research study.

The satisfaction of using a specific type of technology, known as the hedonic motivation, is important in a consumer accepting technology (Brown & Venkatesh, 2005). The price value of technology usage also impacts how the consumer adapts; for example, if the price is too high, the consumer does not adapt (Chang, 2012). The remaining construct of UTAUT2 is the consumer's habit of changing the behaviors of accepting new technology. Kruglanski and Szumowska (2020) defined habitual behaviors as goal-driven and learned over some time.

THEORY OF ECONOMIC DEVELOPMENT

Throughout the existence of humans, needs have changed, and we have evolved. As our needs have changed our development of the economy has also evolved. The theory of economic development was introduced by Schumpeter, who found that economic development is based off the business cycle (Pelsa & Belini, 2022).

The theory of economic development has four major elements. The first element, circular flow, is the basics of supply and demand (Emami-Langroodi, 2017). The second is the role of the entrepreneur, where the entrepreneur will take a risk or provide leadership in introducing the AI innovation (Emami-Langroodi, 2017). The third element is the business cycle, which assesses itself to capitalism which is the "process by which economic life adapts itself to the new economic conditions" (Schumpeter, 1961). The fourth and final element of the economic development theory is capitalism's end (Emami-Langroodi, 2017).

TECHNOLOGY ACCEPTANCE MODEL

The technology acceptance model was introduced in 1986 and was once considered an influential and common theory to describe someone's acceptance of a specific technology (Davis, 1986). The technology acceptance model depends on two variables: perceived usefulness and perceived ease of use (Lee et al., 2003). This theory helps to identify the gaps of the previous research as to the "why" someone will accept or decline AI innovation.

INNOVATION RESISTANCE THEORY

AI Innovation resistance theory was discussed first in the seminal works by Ram (1987) but later modified by Ram and Sheth (1989) to describe why consumers resist new AI innovations. In the seminal works of Ram and Sheth (1989), they stated that a consumer will resist innovations if the AI innovation changes their lifestyle and status. A simple version of innovation resistance theory, known as *active* AI *innovation resistance*, can be defined as a pessimistic view that does not meet users' tolerance and gives a negative attitude towards the AI innovation (Sadiq et al., 2021) and is a main driver for AI innovation rejection (Joachim et al., 2017).

AI Innovation resistance theory and active AI innovation resistance used in the theoretical foundation as reasonings for consumers and employees to reject AI innovations that could improve the overall easiness of a job function or quality of life. Both AI innovation resistance theory and active AI innovation resistance have three similar foundations of AI innovation rejection: postponement, opposition, or outright rejection (Szmigin & Foxall, 1998).

RESEARCH HYPOTHESIS AND RESEARCH STUDY RESULTS

The geographical area for this research is the United States. The two variables we examined were what investments are considered at an organization: AI innovation and the consumer user acceptance of innovative technologies. Consumer user acceptance of AI innovative technologies was the dependent variable, and the AI innovation category was the predictor variable. In using the perceived usefulness and perceived ease of use, we were able to measure the results of this study using the technology acceptance model.

H_a1: *A relationship exists between management artificial intelligence AI innovation and an organization's performance in the United States.*

H_a2: *There is a relationship between AI innovation management and consumer acceptance of AI innovative technologies in the United States.*

Table 1 summarizes the collection information for the survey conducted. As described in table 1, the survey would be opened until the 40-participant rate was met. It took 4 days total for the survey to reach its minimum participation rate. After the minimum participation rate was met, the survey was closed, and data were no longer collected after May 23, 2023.

TABLE 1
DATA COLLECTION SUMMARY

Survey post on LinkedIn	Response rate	End date	Days
5/19/2023	38	05/21/2023	2
5/22/2023	2	5/23/2023	2

Originally, participants were to be asked to provide their responses within 72 hours of receiving their request of the survey, but because an invitation was not sent via email, another LinkedIn post was shared with the link to the research study within 72 hours of the initial post recruiting for this research study.

The research survey consisted of 20 questions. The final two questions of the survey were open-ended for the participant to write as much or as little as they desired describing what products or services the participant easily accepts and what products or services the participant struggles to accept. The survey had a 100% response rate, but the last two open-ended questions were answered by 31/40 respondents.

A Pearson correlation analysis was conducted among Q1LaunchProducts, Q2RangeOfProNotOffered, Q3AddNewProducts, Q4ImproveProducts, Q5ChangeProducts, Q6Reposition, Q7Profitable, Q8MoreMarketShare, Q9RapidGrowth, Q10PerformancePrevious12Months, Q11PerformancePrevious60Months, Q12PerformanceMetPrevious12Months, and Q13PerformanceMetPrevious60Months. Cohen's standard was used to evaluate the strength of the relationships, where coefficients between .10 and .29 represent a small effect size, coefficients between .30 and .49 represent a moderate effect size, and coefficients above .50 indicate a large effect size (Cohen, 1988).

A Pearson correlation requires linear relationship between each pair of variables (Conover & Iman, 1981). This assumption is violated if there is curvature among the points on the scatterplot between any pair of variables. Tables presents the scatterplots of the correlations. A regression line has been added to assist the interpretation. A Mardia's test was conducted for each pair of variables to determine if a bivariate normal distribution could have produced the variable pairings. The results of Mardia's test was significant based on an alpha value of .05 for the following variable pairings and suggests that it is unlikely for the variable pairings to have been produced by a bivariate normal distribution: Q1LaunchProducts-Q2RangeOfProNotOffered (p_{skew} = .008, p_{kurt} = .024), Q2RangeOfProNotOffered-Q3AddNewProducts (p_{skew} = .005, p_{kurt} = .101), Q2RangeOfProNotOffered-Q4ImproveProducts (p_{skew} = .048, p_{kurt} = .119), Q2RangeOfProNotOffered-Q6Reposition (p_{skew} = .026, p_{kurt} = .613), Q2RangeOfProNotOffered-Q7Profitable (p_{skew} = .018, p_{kurt} = .384), Q2RangeOfProNotOffered-Q10PerformancePrevious12Months (p_{skew} = .022, p_{kurt} = .811), Q2RangeOfProNotOffered-Q11PerformancePrevious60Months (p_{skew} = .032, p_{kurt} = .573), Q2RangeOfProNotOffered-Q12PerformanceMetPrevious12Months (p_{skew} = .015, p_{kurt} = .865), Q2RangeOfProNotOffered-Q13PerformanceMetPrevious60Months (p_{skew} = .007, p_{kurt} = .970), Q3AddNewProducts-Q5ChangeProducts (p_{skew} = .005, p_{kurt} = .649), Q3AddNewProducts-Q6Reposition (p_{skew} = .009, p_{kurt} = .101), Q3AddNewProducts-Q7Profitable (p_{skew} = .024, p_{kurt} = .960), Q3AddNewProducts-Q10PerformancePrevious12Months (p_{skew} = .009, p_{kurt} = .575), Q5ChangeProducts-Q12PerformanceMetPrevious12Months (p_{skew} = .023, p_{kurt} = .789), Q7Profitable-Q10PerformancePrevious12Months (p_{skew} = .015, p_{kurt} = .209), Q7Profitable-Q13PerformanceMetPrevious60Months (p_{skew} = .041, p_{kurt} = .099), and Q12PerformanceMetPrevious12Months-Q13PerformanceMetPrevious60Months (p_{skew} = .010, p_{kurt} = .212). This indicates that the bivariate normality assumption is violated. The results of the Mardia's test can be found in Table 2.

TABLE 2
MARDIA'S TEST RESULTS FOR EACH VARIABLE PAIRING

Combination	Skew statistic	p_{skew}	Kurtosis statistic	p_{kurt}
Q1LaunchProducts-Q2RangeOfProNotOffered	13.81	.008	2.25	.024
Q1LaunchProducts-Q3AddNewProducts	5.39	.250	-0.55	.585
Q1LaunchProducts-Q4ImproveProducts	2.01	.734	-1.12	.263
Q1LaunchProducts-Q5ChangeProducts	4.35	.361	-0.85	.396
Q1LaunchProducts-Q6Reposition	1.40	.845	-0.83	.405
Q1LaunchProducts-Q7Profitable	3.77	.438	-0.24	.809
Q1LaunchProducts-Q8MoreMarketShare	5.32	.256	-0.63	.530
Q1LaunchProducts-Q9RapidGrowth	4.73	.316	-1.35	.176
Q1LaunchProducts-Q10PerformancePrevious12Months	2.35	.671	-1.19	.236
Q1LaunchProducts-Q11PerformancePrevious60Months	2.45	.654	-1.45	.147
Q1LaunchProducts-Q12PerformanceMetPrevious12Months	2.00	.736	-0.82	.413
Q1LaunchProducts-Q13PerformanceMetPrevious60Months	4.07	.397	-0.54	.588
Q2RangeOfProNotOffered-Q3AddNewProducts	14.72	.005	1.64	.101
Q2RangeOfProNotOffered-Q4ImproveProducts	9.58	.048	1.56	.119
Q2RangeOfProNotOffered-Q5ChangeProducts	7.21	.125	0.01	.990
Q2RangeOfProNotOffered-Q6Reposition	11.06	.026	0.51	.613
Q2RangeOfProNotOffered-Q7Profitable	11.89	.018	0.87	.384
Q2RangeOfProNotOffered-Q8MoreMarketShare	5.59	.232	0.83	.404
Q2RangeOfProNotOffered-Q9RapidGrowth	8.31	.081	0.74	.458
Q2RangeOfProNotOffered-Q10PerformancePrevious12Months	11.47	.022	-0.24	.811
Q2RangeOfProNotOffered-Q11PerformancePrevious60Months	10.59	.032	-0.56	.573
Q2RangeOfProNotOffered-Q12PerformanceMetPrevious12Months	12.30	.015	-0.17	.865
Q2RangeOfProNotOffered-Q13PerformanceMetPrevious60Months	14.22	.007	0.04	.970
Q3AddNewProducts-Q4ImproveProducts	6.61	.158	-0.02	.986
Q3AddNewProducts-Q5ChangeProducts	15.08	.005	0.45	.649
Q3AddNewProducts-Q6Reposition	13.55	.009	1.64	.101
Q3AddNewProducts-Q7Profitable	11.23	.024	0.05	.960

Combination	Skew statistic	p_{skew}	Kurtosis statistic	p_{kurt}
Q3AddNewProducts-Q8MoreMarketShare	7.54	.110	0.66	.511
Q3AddNewProducts-Q9RapidGrowth	9.09	.059	0.66	.509
Q3AddNewProducts-Q10PerformancePrevious12Months	13.56	.009	-0.56	.575
Q3AddNewProducts-Q11PerformancePrevious60Months	7.74	.102	-0.58	.559
Q3AddNewProducts-Q12PerformanceMetPrevious12Months	9.18	.057	-0.13	.894
Q3AddNewProducts-Q13PerformanceMetPrevious60Months	8.90	.064	-0.16	.876
Q4ImproveProducts-Q5ChangeProducts	6.10	.192	-0.54	.587
Q4ImproveProducts-Q6Reposition	3.44	.487	-0.41	.682
Q4ImproveProducts-Q7Profitable	4.11	.391	-0.08	.935
Q4ImproveProducts-Q8MoreMarketShare	2.82	.589	-0.53	.593
Q4ImproveProducts-Q9RapidGrowth	2.83	.588	-1.13	.260
Q4ImproveProducts-Q10PerformancePrevious12Months	6.15	.188	-1.04	.300
Q4ImproveProducts-Q11PerformancePrevious60Months	6.53	.163	-0.91	.360
Q4ImproveProducts-Q12PerformanceMetPrevious12Months	7.63	.106	-0.52	.602
Q4ImproveProducts-Q13PerformanceMetPrevious60Months	6.30	.178	-0.69	.492
Q5ChangeProducts-Q6Reposition	3.80	.434	-0.16	.876
Q5ChangeProducts-Q7Profitable	4.35	.361	0.04	.970
Q5ChangeProducts-Q8MoreMarketShare	4.97	.290	-0.79	.429
Q5ChangeProducts-Q9RapidGrowth	4.75	.314	-0.41	.680
Q5ChangeProducts-Q10PerformancePrevious12Months	4.09	.394	-0.69	.491
Q5ChangeProducts-Q11PerformancePrevious60Months	4.40	.354	-0.84	.402
Q5ChangeProducts-Q12PerformanceMetPrevious12Months	11.32	.023	0.27	.789
Q5ChangeProducts-Q13PerformanceMetPrevious60Months	6.31	.177	-0.63	.525
Q6Reposition-Q7Profitable	2.40	.663	-0.03	.976
Q6Reposition-Q8MoreMarketShare	2.35	.671	-0.47	.642
Q6Reposition-Q9RapidGrowth	4.90	.298	-0.18	.855
Q6Reposition-Q10PerformancePrevious12Months	2.72	.606	-1.02	.307
Q6Reposition-Q11PerformancePrevious60Months	5.00	.287	-0.96	.339
Q6Reposition-Q12PerformanceMetPrevious12Months	3.13	.536	-0.94	.348
Q6Reposition-Q13PerformanceMetPrevious60Months	4.51	.341	-0.75	.453
Q7Profitable-Q8MoreMarketShare	6.10	.192	0.22	.824
Q7Profitable-Q9RapidGrowth	6.42	.170	-0.02	.983
Q7Profitable-Q10PerformancePrevious12Months	12.41	.015	1.26	.209
Q7Profitable-Q11PerformancePrevious60Months	4.39	.356	0.10	.923
Q7Profitable-Q12PerformanceMetPrevious12Months	6.97	.137	1.02	.309
Q7Profitable-Q13PerformanceMetPrevious60Months	9.96	.041	1.65	.099
Q8MoreMarketShare-Q9RapidGrowth	3.73	.444	-0.44	.661
Q8MoreMarketShare-Q10PerformancePrevious12Months	4.12	.390	-0.56	.575
Q8MoreMarketShare-Q11PerformancePrevious60Months	5.35	.253	-1.07	.285

Combination	Skew statistic	p_{skew}	Kurtosis statistic	p_{kurt}
Q8MoreMarketShare-Q12PerformanceMetPrevious12Months	3.40	.494	-0.36	.715
Q8MoreMarketShare-Q13PerformanceMetPrevious60Months	4.97	.291	-0.45	.653
Q9RapidGrowth-Q10PerformancePrevious12Months	2.64	.620	-1.32	.188
Q9RapidGrowth-Q11PerformancePrevious60Months	6.68	.154	-0.08	.936
Q9RapidGrowth-Q12PerformanceMetPrevious12Months	4.50	.342	-0.47	.636
Q9RapidGrowth-Q13PerformanceMetPrevious60Months	3.62	.459	-0.81	.419
Q10PerformancePrevious12Months-Q11PerformancePrevious60Months	4.70	.320	-1.17	.244
Q10PerformancePrevious12Months-Q12PerformanceMetPrevious12Months	2.75	.601	-1.10	.270
Q10PerformancePrevious12Months-Q13PerformanceMetPrevious60Months	3.50	.478	-1.08	.282
Q11PerformancePrevious60Months-Q12PerformanceMetPrevious12Months	4.08	.395	-0.51	.610
Q11PerformancePrevious60Months-Q13PerformanceMetPrevious60Months	5.84	.211	-0.82	.413
Q12PerformanceMetPrevious12Months-Q13PerformanceMetPrevious60Months	13.17	.010	1.25	.212

The result of the correlations was examined using the Holm correction to adjust for multiple comparisons based on an alpha value of .05. A significant positive correlation was observed between Q2RangeOfProNotOffered and Q3AddNewProducts, with a correlation of .55, indicating a large effect size (p = .018, 95.00% CI = [.28, .73]). This suggests that as Q2RangeOfProNotOffered increases, Q3AddNewProducts tends to increase. A significant positive correlation was observed between Q5ChangeProducts and Q6Reposition, with a correlation of .53, indicating a large effect size (p = .030, 95.00% CI = [.26, .72]). This suggests that as Q5ChangeProducts increases, Q6Reposition tends to increase. A significant positive correlation was observed between Q6Reposition and Q12PerformanceMetPrevious12Months, with a correlation of .51, indicating a large effect size (p = .048, 95.00% CI = [.24, .71]). This suggests that as Q6Reposition increases, Q12PerformanceMetPrevious12Months tends to increase. A significant positive correlation was observed between Q6Reposition and Q13PerformanceMetPrevious60Months, with a correlation of .58, indicating a large effect size (p = .007, 95.00% CI = [.32, .75]). This suggests that as Q6Reposition increases, Q13PerformanceMetPrevious60Months tends to increase.

A significant positive correlation was observed between Q7Profitable and Q8MoreMarketShare, with a correlation of .76, indicating a large effect size (p < .001, 95.00% CI = [.58, .86]). This suggests that as Q7Profitable increases, Q8MoreMarketShare tends to increase. A significant positive correlation was observed between Q7Profitable and Q9RapidGrowth, with a correlation of .57, indicating a large effect size (p = .009, 95.00% CI = [.31, .75]). This suggests that as Q7Profitable increases, Q9RapidGrowth tends to increase. A significant positive correlation was observed between Q8MoreMarketShare and Q9RapidGrowth, with a correlation of .64, indicating a large effect size (p < .001, 95.00% CI = [.41, .79]). This suggests that as Q8MoreMarketShare increases, Q9RapidGrowth tends to increase. A significant positive correlation was observed between Q9RapidGrowth and Q10PerformancePrevious12Months, with a correlation of .52, indicating a large effect size (p = .035, 95.00% CI = [.25, .72]). This suggests that as Q9RapidGrowth increases, Q10PerformancePrevious12Months tends to increase. A significant positive correlation was observed between Q9RapidGrowth and Q11PerformancePrevious60Months, with a correlation of .53, indicating a large effect size (*p* = .032, 95.00% CI = [.26, .72]). This suggests that as Q9RapidGrowth increases, Q11PerformancePrevious60Months tends to increase.

A significant positive correlation was observed between Q10PerformancePrevious12Months and Q11PerformancePrevious60Months, with a correlation of .58, indicating a large effect size (*p* = .007, 95.00% CI = [.32, .75]). This suggests that as Q10PerformancePrevious12Months increases, Q11PerformancePrevious60Months tends to increase. A significant positive correlation was observed between Q10PerformancePrevious12Months and Q12PerformanceMetPrevious12Months, with a correlation of .67, indicating a large effect size (*p* < .001, 95.00% CI = [.45, .81]). This suggests that as Q10PerformancePrevious12Months increases, Q12PerformanceMetPrevious12Months tends to increase.

Another significant positive correlation was observed between Q11PerformancePrevious60Months and Q12PerformanceMetPrevious12Months, with a correlation of .59, indicating a large effect size (*p* = .005, 95.00% CI = [.34, .76]). This suggests that as Q11PerformancePrevious60Months increases, Q12PerformanceMetPrevious12Months tends to increase. A significant positive correlation was observed between Q11PerformancePrevious60Months and Q13PerformanceMetPrevious60Months, with a correlation of .67, indicating a large effect size (*p* < .001, 95.00% CI = [.45, .81]). This suggests that as Q11PerformancePrevious60Months increases, Q13PerformanceMetPrevious60Months tends to increase. The final significant positive correlation was observed between Q12PerformanceMetPrevious12Months and Q13PerformanceMetPrevious60Months, with a correlation of .72, indicating a large effect size (*p* < .001, 95.00% CI = [.53, .84]). This suggests that as Q12PerformanceMetPrevious12Months increases, Q13PerformanceMetPrevious60Months tends to increase. No other significant correlations were found. Table 3 and Table 4 present the results of the correlations.

TABLE 3
PEARSON CORRELATION MATRIX AMONG Q1LAUNCHPRODUCTS, Q2RANGEOFPRONOTOFFERED, Q3ADDNEWPRODUCTS, Q4IMPROVEPRODUCTS, Q5CHANGEPRODUCTS, Q6REPOSITION, Q7PROFITABLE, Q8MOREMARKETSHARE,Q9RAPIDGROWTH, Q10PERFORMANCEPREVIOUS12MONTHS, Q11PERFORMANCEPREVIOUS60MONTHS, Q12PERFORMANCEMETPREVIOUS12MONTHS, AND Q13PERFORMANCEMETPREVIOUS60MONTHS

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Q1LaunchProducts	-												
2. Q2RangeOfProNotOffered	.15	-											
3. Q3AddNewProducts	.22	.55*	-										
4. Q4ImproveProducts	.20	.47	.35	-									
5. Q5ChangeProducts	-.11	.27	.38	.19	-								
6. Q6Reposition	.11	.30	.41	.22	.53*	-							
7. Q7Profitable	.26	.18	.03	.24	.02	.30	-						
8. Q8MoreMarketShare	.29	.15	-.01	.29	.11	.19	.76*	-					
9. Q9RapidGrowth	.26	.21	.15	.38	.07	.31	.57*	.64*	-				
10. Q10PerformancePrevious12Months	.18	.32	.32	.42	.24	.45	.37	.24	.52*	-			
11. Q11PerformancePrevious60Months	.15	.04	.03	.16	.05	.34	.26	.03	.53*	.58*	-		
12. Q12PerformanceMetPrevious12Months	-.06	.32	.24	.39	.36	.51*	.26	.15	.41	.67*	.59*	-	
13. Q13PerformanceMetPrevious60Months	-.15	.17	.16	.37	.32	.58*	.34	.12	.44	.51	.67*	.72*	-

Note. $^{*}p$

TABLE 4
PEARSON CORRELATION RESULTS AMONG Q1LAUNCHPRODUCTS, Q2RANGEOFPRONOTOFFERED, Q3ADDNEWPRODUCTS, Q4IMPROVEPRODUCTS, Q5CHANGEPRODUCTS, Q6REPOSITION, Q7PROFITABLE, Q8MOREMARKETSHARE, Q9RAPIDGROWTH, Q10PERFORMANCEPREVIOUS12MONTHS, Q11PERFORMANCEPREVIOUS60MONTHS, Q12PERFORMANCEMETPREVIOUS12MONTHS, AND Q13PERFORMANCEMETPREVIOUS60MONTHS

Combination	*r*	95.00% CI	*n*	*p*
Q1LaunchProducts-Q2RangeOfProNotOffered	.15	[-.17, .44]	40	1.000
Q1LaunchProducts-Q3AddNewProducts	.22	[-.10, .50]	40	1.000
Q1LaunchProducts-Q4ImproveProducts	.20	[-.12, .48]	40	1.000
Q1LaunchProducts-Q5ChangeProducts	-.11	[-.41, .21]	40	1.000
Q1LaunchProducts-Q6Reposition	.11	[-.21, .41]	40	1.000
Q1LaunchProducts-Q7Profitable	.26	[-.06, .53]	40	1.000
Q1LaunchProducts-Q8MoreMarketShare	.29	[-.03, .55]	40	1.000
Q1LaunchProducts-Q9RapidGrowth	.26	[-.06, .53]	40	1.000
Q1LaunchProducts-Q10PerformancePrevious12Months	.18	[-.14, .47]	40	1.000
Q1LaunchProducts-Q11PerformancePrevious60Months	.15	[-.17, .44]	40	1.000
Q1LaunchProducts-Q12PerformanceMetPrevious12Months	-.06	[-.37, .25]	40	1.000
Q1LaunchProducts-Q13PerformanceMetPrevious60Months	-.15	[-.44, .17]	40	1.000
Q2RangeOfProNotOffered-Q3AddNewProducts	.55	[.28, .73]	40	.018
Q2RangeOfProNotOffered-Q4ImproveProducts	.47	[.18, .68]	40	.156
Q2RangeOfProNotOffered-Q5ChangeProducts	.27	[-.04, .54]	40	1.000
Q2RangeOfProNotOffered-Q6Reposition	.30	[-.01, .56]	40	1.000
Q2RangeOfProNotOffered-Q7Profitable	.18	[-.14, .46]	40	1.000
Q2RangeOfProNotOffered-Q8MoreMarketShare	.15	[-.17, .44]	40	1.000
Q2RangeOfProNotOffered-Q9RapidGrowth	.21	[-.11, .49]	40	1.000
Q2RangeOfProNotOffered-Q10PerformancePrevious12Months	.32	[.01, .57]	40	1.000
Q2RangeOfProNotOffered-Q11PerformancePrevious60Months	.04	[-.28, .35]	40	1.000
Q2RangeOfProNotOffered-Q12PerformanceMetPrevious12Months	.32	[.01, .58]	40	1.000
Q2RangeOfProNotOffered-Q13PerformanceMetPrevious60Months	.17	[-.15, .46]	40	1.000
Q3AddNewProducts-Q4ImproveProducts	.35	[.05, .60]	40	1.000
Q3AddNewProducts-Q5ChangeProducts	.38	[.08, .62]	40	.806
Q3AddNewProducts-Q6Reposition	.41	[.12, .64]	40	.463
Q3AddNewProducts-Q7Profitable	.03	[-.28, .34]	40	1.000
Q3AddNewProducts-Q8MoreMarketShare	-.01	[-.32, .30]	40	1.000
Q3AddNewProducts-Q9RapidGrowth	.15	[-.17, .44]	40	1.000
Q3AddNewProducts-Q10PerformancePrevious12Months	.32	[.01, .57]	40	1.000
Q3AddNewProducts-Q11PerformancePrevious60Months	.03	[-.28, .34]	40	1.000
Q3AddNewProducts-Q12PerformanceMetPrevious12Months	.24	[-.08, .51]	40	1.000
Q3AddNewProducts-Q13PerformanceMetPrevious60Months	.16	[-.16, .45]	40	1.000

Combination	*r*	95.00% CI	*n*	*p*
Q4ImproveProducts-Q5ChangeProducts	.19	[-.13, .47]	40	1.000
Q4ImproveProducts-Q6Reposition	.22	[-.10, .50]	40	1.000
Q4ImproveProducts-Q7Profitable	.24	[-.07, .52]	40	1.000
Q4ImproveProducts-Q8MoreMarketShare	.29	[-.03, .55]	40	1.000
Q4ImproveProducts-Q9RapidGrowth	.38	[.08, .62]	40	.816
Q4ImproveProducts-Q10PerformancePrevious12Months	.42	[.12, .65]	40	.432
Q4ImproveProducts-Q11PerformancePrevious60Months	.16	[-.16, .45]	40	1.000
Q4ImproveProducts-Q12PerformanceMetPrevious12Months	.39	[.09, .62]	40	.750
Q4ImproveProducts-Q13PerformanceMetPrevious60Months	.37	[.07, .61]	40	.990
Q5ChangeProducts-Q6Reposition	.53	[.26, .72]	40	.030
Q5ChangeProducts-Q7Profitable	.02	[-.29, .33]	40	1.000
Q5ChangeProducts-Q8MoreMarketShare	.11	[-.21, .41]	40	1.000
Q5ChangeProducts-Q9RapidGrowth	.07	[-.25, .38]	40	1.000
Q5ChangeProducts-Q10PerformancePrevious12Months	.24	[-.08, .51]	40	1.000
Q5ChangeProducts-Q11PerformancePrevious60Months	.05	[-.27, .35]	40	1.000
Q5ChangeProducts-Q12PerformanceMetPrevious12Months	.36	[.05, .60]	40	1.000
Q5ChangeProducts-Q13PerformanceMetPrevious60Months	.32	[.01, .57]	40	1.000
Q6Reposition-Q7Profitable	.30	[-.01, .56]	40	1.000
Q6Reposition-Q8MoreMarketShare	.19	[-.13, .48]	40	1.000
Q6Reposition-Q9RapidGrowth	.31	[-.00, .57]	40	1.000
Q6Reposition-Q10PerformancePrevious12Months	.45	[.16, .66]	40	.249
Q6Reposition-Q11PerformancePrevious60Months	.34	[.04, .59]	40	1.000
Q6Reposition-Q12PerformanceMetPrevious12Months	.51	[.24, .71]	40	.048
Q6Reposition-Q13PerformanceMetPrevious60Months	.58	[.32, .75]	40	.007
Q7Profitable-Q8MoreMarketShare	.76	[.58, .86]	40	< .001
Q7Profitable-Q9RapidGrowth	.57	[.31, .75]	40	.009
Q7Profitable-Q10PerformancePrevious12Months	.37	[.07, .61]	40	.982
Q7Profitable-Q11PerformancePrevious60Months	.26	[-.06, .53]	40	1.000
Q7Profitable-Q12PerformanceMetPrevious12Months	.26	[-.05, .53]	40	1.000
Q7Profitable-Q13PerformanceMetPrevious60Months	.34	[.03, .59]	40	1.000
Q8MoreMarketShare-Q9RapidGrowth	.64	[.41, .79]	40	< .001
Q8MoreMarketShare-Q10PerformancePrevious12Months	.24	[-.08, .51]	40	1.000
Q8MoreMarketShare-Q11PerformancePrevious60Months	.03	[-.28, .34]	40	1.000
Q8MoreMarketShare-Q12PerformanceMetPrevious12Months	.15	[-.17, .44]	40	1.000
Q8MoreMarketShare-Q13PerformanceMetPrevious60Months	.12	[-.20, .41]	40	1.000
Q9RapidGrowth-Q10PerformancePrevious12Months	.52	[.25, .72]	40	.035
Q9RapidGrowth-Q11PerformancePrevious60Months	.53	[.26, .72]	40	.032
Q9RapidGrowth-Q12PerformanceMetPrevious12Months	.41	[.12, .64]	40	.463
Q9RapidGrowth-Q13PerformanceMetPrevious60Months	.44	[.15, .66]	40	.275

Combination	r	95.00% CI	n	p
Q10PerformancePrevious12Months-Q11PerformancePrevious60Months	.58	[.32, .75]	40	.007
Q10PerformancePrevious12Months-Q12PerformanceMetPrevious12Months	.67	[.45, .81]	40	< .001
Q10PerformancePrevious12Months-Q13PerformanceMetPrevious60Months	.51	[.23, .71]	40	.055
Q11PerformancePrevious60Months-Q12PerformanceMetPrevious12Months	.59	[.34, .76]	40	.005
Q11PerformancePrevious60Months-Q13PerformanceMetPrevious60Months	.67	[.45, .81]	40	< .001
Q12PerformanceMetPrevious12Months-Q13PerformanceMetPrevious60Months	.72	[.53, .84]	40	< .001

Note. *p*-values adjusted using the Holm correction.

A Pearson correlation analysis was conducted among Q1LaunchProducts, Q2RangeOfProNotOffered, Q3AddNewProducts, Q4ImproveProducts, Q5ChangeProducts, Q15ConsumerAcceptNew, Q16ConsumerDissatisfiedProvideFeedback, Q17ConsumerAlwaysHasNewProducts, and Q18ConsumerAcceptionFirst. Cohen's standard was used to evaluate the strength of the relationships, where coefficients between .10 and .29 represent a small effect size, coefficients between .30 and .49 represent a moderate effect size, and coefficients above .50 indicate a large effect size (Cohen, 1988). A Pearson correlation requires that the relationship between each pair of variables is linear (Conover & Iman, 1981). This assumption is violated if there is curvature among the points on the scatterplot between any pair of variables. Tables presents the scatterplots of the correlations. A regression line has been added to assist the interpretation.

Some authors also consider bivariate normality to be an assumption of the Pearson correlation coefficient (Bonett & Wright, 2000; Chok, 2010). Bivariate normality was assessed by plotting the squared Mahalanobis distances for each pair of variables against the quantiles of a Chi-square distribution (DeCarlo, 1997; Field, 2017). In the scatterplot, the solid line represents the theoretical quantiles of a normal distribution. Normality can be assumed if the points form a relatively straight line. The scatterplots for normality are presented in Tables.

A Mardia's test was conducted for each pair of variables to determine if the variable pairings could have been produced by a bivariate normal distribution. The results of Mardia's test was significant based on an alpha value of .05 for the following variable pairings and suggests that it is unlikely for the variable pairings to have been produced by a bivariate normal distribution: Q1LaunchProducts-Q2RangeOfProNotOffered (p_{skew} = .008, p_{kurt} = .024), Q2RangeOfProNotOffered-Q3AddNewProducts (p_{skew} = .005, p_{kurt} = .101), Q2RangeOfProNotOffered-Q4ImproveProducts (p_{skew} = .048, p_{kurt} = .119), Q2RangeOfProNotOffered-Q15ConsumerAcceptNew (p_{skew} = .049, p_{kurt} = .971), Q2RangeOfProNotOffered-Q16ConsumerDissatisfiedProvideFeedback (p_{skew} = .012, p_{kurt} = .231), and Q3AddNewProducts-Q5ChangeProducts (p_{skew} = .005, p_{kurt} = .649). This indicates that the bivariate normality assumption is violated. The results of the Mardia's test can be found in Table 5.

TABLE 5
MARDIA'S TEST RESULTS FOR EACH VARIABLE PAIRING

Combination	Skew Statistic	p_{skew}	Kurtosis Statistic	p_{kurt}
Q1LaunchProducts-Q2RangeOfProNotOffered	13.81	.008	2.25	.024
Q1LaunchProducts-Q3AddNewProducts	5.39	.250	-0.55	.585
Q1LaunchProducts-Q4ImproveProducts	2.01	.734	-1.12	.263
Q1LaunchProducts-Q5ChangeProducts	4.35	.361	-0.85	.396
Q1LaunchProducts-Q15ConsumerAcceptNew	2.03	.730	-1.71	.087
Q1LaunchProducts-Q16ConsumerDissatisfiedProvideFeedback	2.82	.588	-1.20	.230
Q1LaunchProducts-Q17ConsumerAlwaysHasNewProducts	0.97	.915	-1.08	.280
Q1LaunchProducts-Q18ConsumerAcceptionFirst	1.48	.830	-0.94	.349
Q2RangeOfProNotOffered-Q3AddNewProducts	14.72	.005	1.64	.101
Q2RangeOfProNotOffered-Q4ImproveProducts	9.58	.048	1.56	.119
Q2RangeOfProNotOffered-Q5ChangeProducts	7.21	.125	0.01	.990
Q2RangeOfProNotOffered-Q15ConsumerAcceptNew	9.53	.049	-0.04	.971
Q2RangeOfProNotOffered-Q16ConsumerDissatisfiedProvideFeedback	12.86	.012	1.20	.231
Q2RangeOfProNotOffered-Q17ConsumerAlwaysHasNewProducts	6.65	.155	0.01	.988
Q2RangeOfProNotOffered-Q18ConsumerAcceptionFirst	7.00	.136	0.25	.800
Q3AddNewProducts-Q4ImproveProducts	6.61	.158	-0.02	.986
Q3AddNewProducts-Q5ChangeProducts	15.08	.005	0.45	.649
Q3AddNewProducts-Q15ConsumerAcceptNew	5.59	.232	-0.55	.580
Q3AddNewProducts-Q16ConsumerDissatisfiedProvideFeedback	9.46	.051	0.51	.607
Q3AddNewProducts-Q17ConsumerAlwaysHasNewProducts	5.27	.261	-0.85	.395
Q3AddNewProducts-Q18ConsumerAcceptionFirst	6.31	.177	-0.20	.844
Q4ImproveProducts-Q5ChangeProducts	6.10	.192	-0.54	.587
Q4ImproveProducts-Q15ConsumerAcceptNew	2.77	.597	-1.36	.175
Q4ImproveProducts-Q16ConsumerDissatisfiedProvideFeedback	8.47	.076	0.04	.967
Q4ImproveProducts-Q17ConsumerAlwaysHasNewProducts	2.09	.719	-0.73	.465
Q4ImproveProducts-Q18ConsumerAcceptionFirst	6.12	.191	-0.35	.729
Q5ChangeProducts-Q15ConsumerAcceptNew	5.66	.226	-1.33	.185
Q5ChangeProducts-Q16ConsumerDissatisfiedProvideFeedback	6.75	.150	-0.77	.442
Q5ChangeProducts-Q17ConsumerAlwaysHasNewProducts	3.01	.555	-1.54	.123
Q5ChangeProducts-Q18ConsumerAcceptionFirst	5.07	.280	-0.89	.375
Q15ConsumerAcceptNew-Q16ConsumerDissatisfiedProvideFeedback	3.95	.413	-0.70	.487

Q15ConsumerAcceptNew-Q17ConsumerAlwaysHasNewProducts	1.66	.798	-1.76	.078
Q15ConsumerAcceptNew-Q18ConsumerAcceptionFirst	3.29	.510	-1.30	.193
Q16ConsumerDissatisfiedProvideFeedback-Q17ConsumerAlwaysHasNewProducts	6.87	.143	-0.58	.564
Q16ConsumerDissatisfiedProvideFeedback-Q18ConsumerAcceptionFirst	3.89	.421	-0.45	.653
Q17ConsumerAlwaysHasNewProducts-Q18ConsumerAcceptionFirst	4.95	.293	-0.77	.440

Mardia's Test Results

The result of the correlations was examined using the Holm correction to adjust for multiple comparisons based on an alpha value of .05. A significant positive correlation was observed between Q2RangeOfProNotOffered and Q3AddNewProducts, with a correlation of .55, indicating a large effect size (p = .009, 95.00% CI = [.28, .73]). This suggests that as Q2RangeOfProNotOffered increases, Q3AddNewProducts tends to increase. A significant positive correlation was observed between Q15ConsumerAcceptNew and Q17ConsumerAlwaysHasNewProducts, with a correlation of .52, indicating a large effect size (p = .017, 95.00% CI = [.25, .72]). This suggests that as Q15ConsumerAcceptNew increases, Q17ConsumerAlwaysHasNewProducts tends to increase. A significant positive correlation was observed between Q15ConsumerAcceptNew and Q18ConsumerAcceptionFirst, with a correlation of .55, indicating a large effect size (p = .008, 95.00% CI = [.29, .74]). This suggests that as Q15ConsumerAcceptNew increases, Q18ConsumerAcceptionFirst tends to increase. A significant positive correlation was observed between Q17ConsumerAlwaysHasNewProducts and Q18ConsumerAcceptionFirst, with a correlation of .66, indicating a large effect size (p < .001, 95.00% CI = [.44, .81]). This suggests that as Q17ConsumerAlwaysHasNewProducts increases, Q18ConsumerAcceptionFirst tends to increase. No other significant correlations were found. Table 6 and Table 7 present the results of the correlations.

TABLE 6
PEARSON CORRELATION MATRIX AMONG Q1LAUNCHPRODUCTS, Q2RANGEOFPRONOTOFFERED, Q3ADDNEWPRODUCTS, Q4IMPROVEPRODUCTS, Q5CHANGEPRODUCTS, Q15CONSUMERACCEPTNEW, Q16CONSUMERDISSATISFIEDPROVIDEFEEDBACK, Q17CONSUMERALWAYSHASNEWPRODUCTS, AND Q18CONSUMERACCEPTIONFIRST

Variable	1	2	3	4	5	6	7	8	9
1. Q1LaunchProducts	-								
2. Q2RangeOfProNotOffered	.15	-							
3. Q3AddNewProducts	.22	.55*	-						
4. Q4ImproveProducts	.20	.47	.35	-					
5. Q5ChangeProducts	-.11	.27	.38	.19	-				
6. Q15ConsumerAcceptNew	.31	.01	.35	.08	.13	-			
7. Q16ConsumerDissatisfiedProvideFeedback	-.08	.15	.07	.10	.23	-.16	-		
8. Q17ConsumerAlwaysHasNewProducts	.09	.31	.42	.06	.22	.52*	.05	-	
9. Q18ConsumerAcceptionFirst	.30	.21	.37	.24	.22	.55*	.06	.66*	-

Note. *p

TABLE 7
PEARSON CORRELATION RESULTS AMONG Q1LAUNCHPRODUCTS, Q2RANGEOFPRONOTOFFERED, Q3ADDNEWPRODUCTS, Q4IMPROVEPRODUCTS, Q5CHANGEPRODUCTS, Q15CONSUMERACCEPTNEW, Q16CONSUMERDISSATISFIEDPROVIDEFEEDBACK, Q17CONSUMERALWAYSHASNEWPRODUCTS, AND Q18CONSUMERACCEPTIONFIRST

Combination	*r*	95.00% CI	*n*	*p*
Q1LaunchProducts-Q2RangeOfProNotOffered	.15	[-.17, .44]	40	1.000
Q1LaunchProducts-Q3AddNewProducts	.22	[-.10, .50]	40	1.000
Q1LaunchProducts-Q4ImproveProducts	.20	[-.12, .48]	40	1.000
Q1LaunchProducts-Q5ChangeProducts	-.11	[-.41, .21]	40	1.000
Q1LaunchProducts-Q15ConsumerAcceptNew	.31	[-.00, .57]	40	1.000
Q1LaunchProducts-Q16ConsumerDissatisfiedProvideFeedback	-.08	[-.38, .24]	40	1.000
Q1LaunchProducts-Q17ConsumerAlwaysHasNewProducts	.09	[-.23, .39]	40	1.000
Q1LaunchProducts-Q18ConsumerAcceptionFirst	.30	[-.01, .56]	40	1.000
Q2RangeOfProNotOffered-Q3AddNewProducts	.55	[.28, .73]	40	.009
Q2RangeOfProNotOffered-Q4ImproveProducts	.47	[.18, .68]	40	.079
Q2RangeOfProNotOffered-Q5ChangeProducts	.27	[-.04, .54]	40	1.000
Q2RangeOfProNotOffered-Q15ConsumerAcceptNew	.01	[-.30, .32]	40	1.000
Q2RangeOfProNotOffered-Q16ConsumerDissatisfiedProvideFeedback	.15	[-.17, .44]	40	1.000
Q2RangeOfProNotOffered-Q17ConsumerAlwaysHasNewProducts	.31	[-.00, .57]	40	1.000
Q2RangeOfProNotOffered-Q18ConsumerAcceptionFirst	.21	[-.11, .49]	40	1.000
Q3AddNewProducts-Q4ImproveProducts	.35	[.05, .60]	40	.723
Q3AddNewProducts-Q5ChangeProducts	.38	[.08, .62]	40	.432
Q3AddNewProducts-Q15ConsumerAcceptNew	.35	[.05, .60]	40	.723
Q3AddNewProducts-Q16ConsumerDissatisfiedProvideFeedback	.07	[-.25, .37]	40	1.000
Q3AddNewProducts-Q17ConsumerAlwaysHasNewProducts	.42	[.13, .65]	40	.201
Q3AddNewProducts-Q18ConsumerAcceptionFirst	.37	[.07, .61]	40	.544
Q4ImproveProducts-Q5ChangeProducts	.19	[-.13, .47]	40	1.000
Q4ImproveProducts-Q15ConsumerAcceptNew	.08	[-.24, .38]	40	1.000
Q4ImproveProducts-Q16ConsumerDissatisfiedProvideFeedback	.10	[-.22, .40]	40	1.000
Q4ImproveProducts-Q17ConsumerAlwaysHasNewProducts	.06	[-.26, .36]	40	1.000
Q4ImproveProducts-Q18ConsumerAcceptionFirst	.24	[-.08, .51]	40	1.000
Q5ChangeProducts-Q15ConsumerAcceptNew	.13	[-.19, .42]	40	1.000
Q5ChangeProducts-Q16ConsumerDissatisfiedProvideFeedback	.23	[-.09, .50]	40	1.000
Q5ChangeProducts-Q17ConsumerAlwaysHasNewProducts	.22	[-.10, .50]	40	1.000
Q5ChangeProducts-Q18ConsumerAcceptionFirst	.22	[-.09, .50]	40	1.000
Q15ConsumerAcceptNew-Q16ConsumerDissatisfiedProvideFeedback	-.16	[-.45, .16]	40	1.000
Q15ConsumerAcceptNew-Q17ConsumerAlwaysHasNewProducts	.52	[.25, .72]	40	.017

Q15ConsumerAcceptNew-Q18ConsumerAcceptionFirst	.55	[.29, .74]	40	.008
Q16ConsumerDissatisfiedProvideFeedback-Q17ConsumerAlwaysHasNewProducts	.05	[-.27, .36]	40	1.000
Q16ConsumerDissatisfiedProvideFeedback-Q18ConsumerAcceptionFirst	.06	[-.26, .36]	40	1.000
Q17ConsumerAlwaysHasNewProducts-Q18ConsumerAcceptionFirst	.66	[.44, .81]	40	< .001

Note. p-values adjusted using the Holm correction.

Two research questions were analyzed and examined utilizing the IBM SPSS software. The first research question examined in the first research question of what the relationship between AI innovation management and organizational performance is. The first research question of there is a relationship between AI innovation management and organizational performance examined the hypothesis and null hypothesis of there is no relationship between management AI innovation and an organization's performance and the null hypothesis of there is a relationship between management AI innovation and an organization's performance. There was enough evidence presented that to reject the first hypothesis when an organization manages AI innovation, the organization's financial performance increases.

The second research question of what the relationship between AI innovation management and consumer acceptance of AI innovative technologies is had also presented enough evidence that when an organization manages AI innovation, consumers are more likely to accept a new product of service connected to the new AI innovative technologies. In testing the first hypothesis, no relationship between AI innovation management and consumer acceptance of AI innovative technologies was nullified by showing a relationship between AI innovation management and consumer acceptance of AI innovative technologies by using the bivariate correlation with Pearson method.

Finally, comments submitted by the participants were analyzed and found a couple of themes regarding what type of AI products or AI services they easily accept or reject. In their comments about accepting and rejecting, AI technology products and/or services within the past five years were presented in both questions. Because AI technology products and/or services were in both questions of acceptance and rejection, it can only be determined that the types of AI products and/or AI services of being accepted or rejected such as newer services that reduce the correspondence of a live person, or newer AI technology that has not been around long enough or been "proven" to society of its added value.

FINDINGS AND INTERPRETATIONS

We used the bivariate correlation with the Pearson coefficient analysis to determine if there was a relationship between AI innovation management and consumer acceptance of AI innovative technologies, and AI innovation management with an organization's performance. My presentation of both included statistical results where testing assumptions to find the results within the participant data submitted. Below are the three variables used in this research study and an interpretation of the findings for each variable.

This research study found that there is a significance in consumer acceptance of AI innovative technologies when innovation is managed. Nambison et al. (2017) explained that as technologies change, which essentially changes organizations, AI innovation management should be researched to incorporate concepts that reflect and capture the ways in which technologies are changing. Most participants show that consumers are willing to accept innovative products or services that are IT related (Kasztelnik, K. 2020).

Managing AI innovation within an organization, whether a product, service, or even a process, needs a life cycle. When an organization spots an opportunity for AI innovation, it is a way to solve a problem for a consumer; internally or externally (Molloy, 2019). Knowing the type of AI innovation for an organization would be helpful in what is being accepted by a consumer. There are several types of AI innovation: organizational, social, product, open, and disruptive AI innovations to name a few. Other variables tested against the AI innovation management were not significant enough to be able to interpret within each other positively or negatively.

Organizational performance was defined earlier as the ability to achieve the goals and objectives that an organization sets either quarterly, annually, or in their mission statement. An organization's performance is usually measured by the success of profits and the return on assets, equity, sales, and investments (Rahman et al., 2018). Performance of an organization is a key performance measurement of its outcome and, although AI innovation may be risky, AI AI innovation generally has a positive outcome for an organization's performance (Walker et al., 2015).

The method Furr and Dyer (2014) found that was successful in adapting AI innovation within an organization were to follow the steps of: (a) insight, (b) problem, (c) solution, (d) business model, and (d) scale it (p. 19). Furr and Dyer also found that, for publicly traded companies that adopted AI innovation elements, within 3–5 years of adoption, their AI innovation premium scores rose over 57% (p. 21).

In this research study, it was found that when AI innovation is managed, there is a significance in organizational performance. Ross and Beath (2002) provide an IT framework, showing that improving a process equals long-term growth. This research study did not focus on an organization's long-term growth, so we cannot confirm that statement. Further research into this statement will be discussed in the limitations of this research study below.

When comparing the organizational performance variables to AI innovation management and consumer acceptance of AI innovative technologies, several factors were noticed. When newer products or services were added to the organizations, the organization performance from the previous 12 months and 60 months variables increased significantly. Other variables tested against the organizational performance were not significant enough to be able to interpret within each other positively or negatively.

The findings of this research may reduce a gap by providing an understanding of how organizations can better manage AI innovation and forecast organizational performance to increase product or service delivery sales using newer innovative technologies. Corporate executive teams do not allocate a significant budget for resources that are towards a strategic corporate AI innovation system (Prahalad & Hamel, 1990); approximately 6% of corporate management teams are satisfied with their AI innovation performance (Hamel & Tennant, 2015). Organizations may be able to better understand how and what to focus on for their consumers by understanding what is acceptable versus unacceptable. Organizations may also be able to better understand how and what to focus on for their employees by understanding what type of AI innovation is accepted versus not accepted by employees to make their organization a better place to work.

The results of this study may help organizations manage AI innovation in providing better organization performance while determining what resources should be invested in and which technologies should be aged out. The research study may also help organizations be more profitable and successful in sustaining the innovative technologies that are deployed to consumers and their employees.

Findings of this study contribute to the technological advances of how to manage AI innovation and the ability to increase the organization's performance. Showing the relationship between the variables of AI innovation management and organization performance can help organizations become innovative and increase their quarterly profits and performance year over year. This information may be of interest to C-level executives to find what would be the best practices in AI innovation management to help their organization find best practices. Other findings may suggest that organizations find alternative AI innovations such as green technology or green AI innovation to create an efficient value chain and increased productivity while being environmentally friendly (Chan, Darko, & Ameyaw, 2017).

The data collected from this research study may assist in finding effective practices for organizations in integrating AI innovations, managing AI innovations, prevent business failure, and improve productivity and profitability. Other significance could result in which IT products or services consumers are more likely to accept or reject and how often a product or service should be updated from the previous versions. The ease of use on a product or service would be able to determine these variables within the research.

CONCLUSION

Several participants stated that they easily accept subscription services that are easy to use on their smart phones. This suggests that the technology acceptance model's two variables are true where the perceived usefulness and perceived ease of use (Lee et al., 2003) are true. Participants stated that innovators easily accept and adopt applications such as delivery food services, easy to use with little to no effort, or those with a trial and/or discount period.

The perceived usefulness and perceived ease of use where software applications that are not easy to use or cause frustration to consumers will not be adopted and further pushed away by laggards and even innovators.

Participants stated that a newer product version is usually not acceptable or worth the cost of upgrading the product. A specific example that was given in the comments by a participant was a product that takes significant time investment before using. Although specific examples of what products participants may have been referring to would have been helpful, the overall theme found was that too many new products being upgraded or updated soon after its original release were not accepted.

Participants rejecting newer versions of products was also noteworthy when participants answered what AI innovations they will typically reject. Newer versions of products were defined as a product that has been available for less than 3 years. Although the research of this study did not go into newer versions of services, it may be beneficial to determine whether newer innovative services are easily rejected too.

This research study aimed to determine whether there is a correlation between AI innovation management and consumer acceptance of AI innovative technologies, and AI innovation management and organizational performance. The literature examined the different types of AI innovation and AI innovation management styles, the types of consumers and which type is most likely to accept or reject innovative products or service such as the innovators and laggards. Most organizations aim to be innovative and do not understand how to define AI innovation (McGowan, 2016). Business managers pursue ways to improve profits and efficiency by integrating AI innovations without preparation and information, which will eventually affect productivity and revenue (Kim & Min, 2015).

Two research questions were analyzed and examined utilizing the IBM SPSS software. The first research question examined the relationship between AI innovation management and organizational performance, with the hypothesis that there is no relationship between management AI innovation and an organization's performance and the null hypothesis of a relationship between management AI innovation and an organization's performance. There was enough evidence presented to reject the first hypothesis when an organization manages AI innovation, the organization's financial performance increases. The second research question of what the relationship between AI innovation management and consumer acceptance of AI innovative technologies is had also presented enough evidence that when an organization manages AI innovation, consumers are more likely to accept a new product of service. In testing the first hypothesis that is no relationship between AI innovation management and consumer acceptance of AI innovative technologies was nullified by showing that there is a relationship between AI innovation management and consumer acceptance of AI innovative technologies by using the bivariate correlation with Pearson method.

Organizations can be more profitable by providing a range of products, planning to provide innovative products and/or services, testing against consumer acceptance of AI innovative technologies criteria, and managing the AI innovation. Organizations have financial goals and when a consumer accepts an innovative idea, product, or service, the organization can either be a disruptor in the industry or go out of business. This research study started with Steve Wozniak's quote and demonstrated that his words are true: "True AI Innovation is one that improves people's lives."

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