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Use of artificial intelligence system to predict consumers' behaviors

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A B S T R A C T

In online shopping enterprises, AI technology has been widely used to provide accurate and fast personalized consumer services. This research demonstrates the use of AI technology in the e-commerce business, specifically online enterprises, to determine different effects. The study was conducted in Jordan and involved about 230 participants. The study evaluated different impacts of AI, such as e-payment and stimulating consumers' sentiments. The study used the Stimulus–Organism–Response model (SOR) empirical model, which states that the examination of human processes differs from that of the machine assessment. The model classified the AI technology experienced by the customers' when they visit online to do purchasing. Online purchasing behaviors can be influenced by insight, accuracy, and interaction experience. Also, the perceived value was used as a mediating variable from the prospects of perceived hedonic and utility value. The research integrated empirical research models such as SEM and SPSS to analyze the data on the effects of three-dimension. The results indicated that the AI technology accuracy, interactive experience, and insight significantly affected customers' perceived hedonic and utilitarian values.

1. Introduction

In modern business, the domination of Artificial Intelligence (AI) profoundly in every business organization is undeniable (André et al., 2015). In addition, Artificial Intelligence is being used to comprehensively predict the customers' behaviors to restore the processes in a business by eliminating redundant tasks. For business organizations, it is relevant to understand consumers' demands and expectations to remain ahead of the competition. In contrast, to the new usual belief that AI will produce the most significant influence on the manufacturing sector, current research reveals that there will be a considerable impact on the consumers' buying behaviors in the retail industries (André et al., 2015). In addition, the E-commerce business is growing at an alarming rate following the advancement of new technology, and many consumers are purchasing products online. Due to this technology revolution, data generation, and retail promotion, businesses and marketers no longer use traditional statistical methods. For example, Fusion Informatics is one of the AI technology companies in Amman, Jordan, that deal with Natural Language Processing (NLP), machine learning, Chatbot development, and predictive analytics (Adwan & Aladwan, 2019). The current research demonstrates an analysis of extensive data mining and processing in business operations and management.

Also, the growth of technology-enhanced extensive data development made AI emerge with high projecting analytics such as data mining and machine learning (Meske et al., 2019). The growth of AI has emerged and impacted how businesses implement their strategic markets to meet their consumers' needs. However, incorporating Artificial Intelligence is considered a complicated process of analyzing the data and decision-making process. Many business organizations consider AI an asset,

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and as a tool, it helps in massive data processing and achieving accurate predictions. Hence, this paper will integrate a structural equation model (SEM) to examine the correlation between Artificial Intelligence and e-commerce online shopping platforms in Jordan and the customers' buying intention and evaluate the mediating role of perceived utilitarian and hedonic values (André et al., 2015). The findings provide an accurate basis for online businesses to evaluate the researched direction of Artificial Intelligence technology and enhance customers' purchasing perceived value to improve online errands services (Gursoy et al., 2019).

2. Literature Review and Theoretical Conceptualization

Research shows that business AI systems and technology are used to select and organize relevant information such as multimedia content, news that customers read, search results, and suggestions for future purchases (Bock et al., 2020) (Yaseen, Al Adwan, Alhorani, Al Adwan & Kokash, 2020). This type of function is considered helpful to customers, specifically because machines tend to be more objective and efficient than human beings in selecting the quality and relevant information. In this case, the algorithms can help overcome overwork or burden by assuming the change of information processing. In addition, AI can change the process of decision-making by making the customers look for the purchasing choices to algorithms, thus creating a perception of the algorithmic consumer (Bock et al., 2020). Comparatively, algorithms help customers to overcome cognitive limits and behavioral bias, make rational choices, and enlighten them against unscrupulous marketing techniques (Al Adwan, Zamil, Areiqat, 2021). For example, the use of Machine learning algorithms in various companies helps develop systems that use consumers' past data to reveal crucial insights concerning consumers' behaviors (Bock et al., 2020).

Bundorf et al. (2019) conducted a study using a measured trial whereby they provided access to the decision support tool integrating algorithmic commendations for selecting the cost-minimizing insurance cover or plan (Bundorf et al., 2019). According to the findings, the algorithmic intelligence escalated the probability of switching the plan. In addition, the researchers revealed that the self-selection in the software used was comprehensively crucial. In addition, many respondents who accepted the algorithmic support were determined to change their insurance plan. This means that incorporating AI systems in business operations such as marketing may influence consumers' behaviors. Bundorf et al. research proposed two hypotheses (Bundorf et al., 2019):

Hypothesis 1: The adoption of the algorithm expert commendations significantly escalates cost savings, choice process satisfaction, time for selecting a plan, and plan to switch (Bundorf et al., 2019).

Hypothesis 2: More active buyers' consumers are able to utilize the decision-making support tool as evidence of self-selection (Bundorf et al., 2019).

2.1 Effective e-Payment Transactions

The growth of technology has made many businesses flourish as they incorporate AI innovations in e-commerce and business transactions (Belanche et al., 2019). A report by Statista Corporation demonstrated that more than 37% of the finance sector globally depends on AI for business transactions and other operations. Also, the report shows that new technology in AI and other innovations is thriving at a high rate, with a global market of more than $ 331 billion. One effect that AI can bring to the business is enhancing consumers' experience (Belanche et al., 2019). In many cases, consumers' experience is one vital success factor in every enterprise, especially e-commerce businesses. However, customers achieve a streamlined e-payment when they incorporate AI in business payment processing since it reduces the transaction screening time and executes the process efficiently. In addition, AI collects information concerning the clients' data to predict the client's next move in the future (Belanche et al., 2019).

Another benefit of AI is preventing or stimulating online fraud detection (Huang & Rust, 2021) previously, consumers used to purchase their products through a manual cash transaction. However, with the growth of AI, consumers can purchase and transact through e-payments methods. A survey shows that AI proves to be an effective method of preventing online fraudulent transactions. Additionally, using machine learning technology, computers can detect suspicious transactions in a large data set. In this case, it is well suited with a mechanism to detect any fraudulent activity and reduce the efforts needed to review the success of every transaction (Huang & Rust, 2021).

Conversely, AI has proved to enhance speed and accuracy during the transaction. For example, the technology can review many transactions within a short time and still maintain accuracy. In this case, consumers can now transact from one merchant to another despite the location and distance since the AI bypasses the need for manual processes (Meske et al., 2019).

Hypothesis 1: The integration of AI positively affects business payment processes, reduces transaction screening, and promotes efficiency (Gursoy, et al., 2019).

Hypothesis 2: The use of AI has a significant effect on detecting online fraud and enhancing customer transaction speed and accuracy (Meske et al., 2019).

2.2 Effective Consumers' Sentiment Analysis

The growth of technology has significantly led to the development of social media platforms such as Facebook, Twitter, and YouTube, where businesses can analyze consumers' sentiments concerning goods and services (Huang & Rust, 2021) (Al Adwan, Zamil, Areiqat, 2021). According to a recent study, online businesses use sentiment analysis such as text to decode consumers' feelings (negative, neutral, or positive) towards particular goods and services. For instance, Artificial Intelligence tools can analyze more than 10000 online reviews concerning a product to help the business realize whether consumers are happy or unhappy with your product's quality and price (Huang & Rust, 2021) (Al Adwan, 2020). In the e-commerce business, interpreting customers' emotional sentiments is critical in business. According to Bill Gates' remarks (Founder of Microsoft), unhappy customers' becomes the most significant source of your learning (Gursoy, et al., 2019). In this case, customers usually post reviews and discuss each aspect of business products and services from price, quality, delivery, and satisfaction on social media platforms. Artificial Intelligence tools take this content from social media to disclose consumers' sentiments concerning enterprise products and services. In addition, AI technology helps to determine consumers' expectations in future. Conversely, based on these views, a business can make a crucial decision to enhance affordability, customer service, and quality (André et al., 2015)

3. Conceptual Framework

3.1 Stimulus–Organism–Response Model (SOR)

Russell and Mehrabian first suggested the SOR model in 1974 (Chang et al., 2011). The model argues that the assessment procedure of human beings differs from that of a machine. According to researchers, various types of incitements in the environment, including olfactory, auditory, and visual stimuli, tend to cause changes in the state of the internal feeling and cognitive mechanism, which later cause a response (Chang et al., 2011). Also, research shows that Donovan and Rossiter become the first people to integrate the SOR model in a shopping field study. In addition, Eroglua et al. incorporated the SOR model into the online errands enterprise to investigate the effects of cognitive state and preference on the online purchasing consumption behaviors in the e-commerce atmosphere. Scholars argue that the space of the online website showed an impact on customers' avoidance or approach behaviors. In addition, the website features (entertainment, security or convenience) will influence the perceived quality and consumer's shopping intention in online enterprise (Chang et al., 2011).

Conversely, the state of customers' emotional feelings, such as impulse and pleasure, can influence the consumption expenditure (Cheung, 2015). Furthermore, research shows that website navigation edifice impacts the shopping intention through customers' participation, risk acceptance, and atmosphere acceptance. Another study by Sanjeev Prasha et al. demonstrates that a website atmosphere comprises internal elements (utilitarian and hedonic shopping value), external elements (information content, website information, or entertainment) and the satisfaction generated by websites to customers correspondingly impact consumers' consumption behaviors. Based on these concepts, the present research on AI technology as the incentives is projected in the exploration of the effectiveness of the network, navigation of the website structure, and the implementation of the platform-assisted enterprise technology (Islam & Rahman, 2017). Currently, AI technology is empowering online businesses, but little research has been conducted on the type of stimulation on customers' consumption behaviors and online shopping intention. In this study, we will analyze the SOR model and SEM to explore the application of AI technology in consumers' online purchasing behaviors (Chang et al., 2011).

3.2 The Consumer Perceived Value

The consumer perceived value entails all the assessment of the perceived differences between customers' payment and obtaining in purchasing (Islam & Rahman, 2017). To explain the concept of consumers' behaviors, a multi-dimensional survey on perceived value would be more specific in demonstrating different consumption situations on customers' preferences than a one-dimensional structure. Additionally, some researchers classify the consumer perceived value as perceived cognitive value, perceived utility value, hedonic and social value (Islam & Rahman, 2017). In a study on consumer perceived value and use of technology systems, a Technology Acceptance Model (TAM) introduced by Davis (1989) sets perceived usefulness and perceived ease as independent variables (Kim & Lennon, 2013). Davis also considers that perceived usefulness and ease will influence consumers' assertiveness towards technology and later impact their behavior. Contrary, perceived utilitarianism involves the utility-related value personification of the customer behavior or the products, including the convenience of use, time costs, and saving. Conversely, perceived hedonic value includes curiosity, pleasure, interactive process, arousal, and mental concentration. AI technology has continued influence on value analysis, algorithm interactions, and stimulation (Cheung, 2015).

3.2.1 Theoretical Model Framework

The following summarizes the proposed study of this paper.

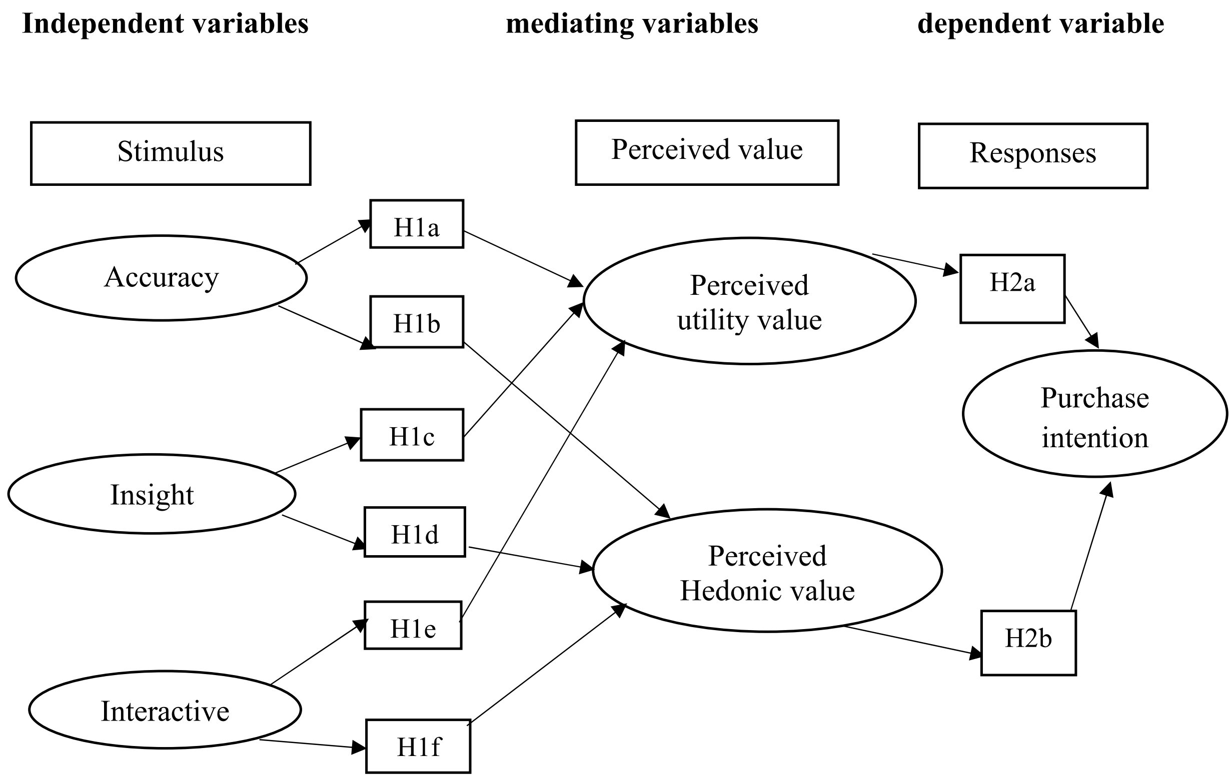

Fig. 1. Research Model

3.3 Hypothesis of the Study

3.3.1 The Consumer Perceived Value and AI Marketing Technology Experience

The adoption of AI technology influences the consumers' stimulation to make complex purchase decisions which help them make good choices, save time, and be more accurate during online shopping (Kumar, et al., 2019). Correspondingly, integrating AI technologies such as machine learning, visual recognition, and speech recognition can enhance practical insight into consumers' behaviors. These insights can produce five aspects: post-purchase evaluation, problem recognition, alternative evaluation, shopping decision-making, and information collection. In this case, the customers will gain more effective consumption and make the entire process's value perception smooth. Hence, the following hypothesis can be deduced (Kumar et al., 2019):

Hypothesis 1**:** The enrichment of the accuracy experience of Artificial Intelligence technology in online purchasing platforms is favorable to stimulating the formation of customers' perceived hedonic and utility value (Kim & Lennon, 2013).

Hypothesis 2: The enhancement of the interactive experience of AI technology in online purchasing platforms is favorable to promoting the formation of customers; perceived hedonic and utility value (Kumar, et al., 2019).

Hypothesis 3: The enrichment of the insight experience of Artificial Intelligence technology in online purchasing platforms is favorable to encouraging the formation of customers' perceived hedonic and perceived utility value (Kumar, et al., 2019).

3.4 Study Design

Most researchers have incorporated experimental designs and questionnaire surveys to conduct AI research. In most cases, the basic hypothesis-testing and data analysis methods incorporate the SEM, T-Test, regression analysis, and Chi-square test. This research will use the Structural equation model and the questionnaire survey to test the hypothesis and data analysis.

3.5 Methodology

3.5.1 The Scale Design

According to previous research, no mature measurement scale is used to evaluate the AI technology experience with the online shopping platforms (Meske et al., 2019). However, the evaluation of the AI technology marketing experience is usually achieved through inclusive research on marketing expert opinions, previous literature reviews, Current AI technology experiences, and actual functional statistics, among other factors. In this study, the scholars evaluated the consumers' Artificial Intelligence technology experience relating to online purchasing platforms from three scopes, interactivity, accuracy and insight. The investigators collected data to evaluate the real experiences from Jordan online errands websites (matjarii.com, AmmaCart, and Jordan Nike.com), which forms the top online e-commerce websites. To measure insight experience, the scholars used the research viewpoints of Qian M, Jordan et al. and V. Kumar et al., who designed a scale interconnected with pertinent functions of online errands platforms for AI technology. In addition, the evaluation of the interactive experience is based on the Jiang Shen scale, which combines the AI customer service functions designs (Kazakeviciute & Banyte, 2012).

The researchers used the Chu Tanming scale to evaluate the data of perceived utility value, while Moon et al. and Yang et al. measured the value of hedonic perceived value (Kazakeviciute & Banyte, 2012). Similarly, Carlota L.R et al. scale measured the value of purchase intention on AI technology. In addition, the questionnaire scale was compiled with 5 points Likert scale items marked with 1 (strongly disagree) and five showing agreement or approval strongly. The scholars conducted two surveys to ensure effectiveness and rationality, the pre-survey and the primary survey. Before the study, two e-commerce enterprise experts and the e-commerce industry were invited to revise and approve the questionnaires to form the final drafts. Also, the scholars eliminated any questionnaire that could consume more than one minute to complete to avoid time wastage and random filing. Comparatively, the study used about 217 valid questionnaires, and the effective rate was 85 per cent. In the pre-survey stage, the study used exploratory analysis for the questionnaire (Lee & Wu, 2017).

3.5.2 Study Population and Sample

The sample data for this research was obtained from the three online enterprises platforms of Jordan's e-commerce enterprises in 2020 (matjarii.com, AmmaCart, and Jordan Nike.com) (Kietzmann et al., 2018). The participants were customers with the online purchasing experience. During the research process, the scholars designed the questionnaires using the Questionnaire Star Platform and the respondents filled in online. The scholars collected 230 questionnaires, and those with repeated answers and shorter than one-minute answers were considered invalid. Finally, 217 valid questionnaires were collected at an effective rate of 92 %, which met the requirement of an adequate data sample more than that of measurement items (Kietzmann et al., 2018). According to the demographic characteristics of the valid questionnaires, 61.01 per cent were females while 38.99 per cent were males in terms of gender analysis (Wu et al., 2014). In terms of age analysis, 38. 50% were between 21- 30 years old, while 3.97% were below 20 years. Also, 45.07% had 31-40 years, 8.41% had 41-50 years, and 3.34% had 51 years and above. In terms of education analysis, 54.2 per cent had Bachelor's degrees, 20.13 per cent were under Bachelor's degrees, and 25.67 per cent had Master's and postgraduate degrees (Wu et al., 2014). In addition, data analysis in terms of online shopping for less than three years accounted for 6.81 per cent, 3 to 6 years accounted for 35.5 per cent, and 7 to 9 years accounted for 28. 05 per cent while more than ten years was represented by 29.64 per cent. Additionally, the data analysis of disposable income below 100 000 accounted for 26. 47percent, 34.39 percent (100,000- 200, 000), 21.24 percent (200,000-300000), and above 300000 accounted for 17.9 percent. In terms of frequency, between 2 and 4 times accounted for 32.65 per cent, while more than five times a day accounted for 5.71 per cent (Lee & Wu, 2017).

Table 1
Demographic Characteristics

Demographic characteristics		Percentage (%)
Age	Below 20 years	3.97%
	21-30	38.50%
	31-40	45.07%
	41-50	9.11%
	Above 51	3.34%
Education	Under Bachelor's degree	20.13%
	Bachelor's degree	54.2%
	Masters and postgraduate	25.67%
Online shopping	Less than 3 years	6.81%
	3-6	35.5 %
	7-9	28.05%
	Above 10 years	29.64%
Disposable income	Below 100000	26.47%
	100000-200000	34.39%
	200000-300000	21.24%
	Above 300000	17.9%
Frequency of online shopping	2-4 times a week	32.65%
	5 times and above	5.71%

4. Data Analysis

During the study, the scholars' utilized the SPSS tests and SPSS 23.0 to analyze the statistical data Lee & Wu, 2017). The researcher's conducted the exploratory factor analysis, reliability test, and validity test of the sample data. In addition, the Structural Equation Model (SEM) was used to perform the confirmatory factor analysis to ensure the model and the sample data achieved profound fitting. Lastly, the study integrated a multi-group path coefficient analysis on the hypothetical model (Lee & Wu, 2017).

4.1 Reliability and Measure Analysis

The investigators used Cronbach's alpha coefficient to evaluate the reliability of the latent variables (Lee & Wu, 2017). As indicated in the table below, the Cronbach's alpha values of the variables in the study ranged between 0.743 and 0.836, and the combined reliability values range between 0.855 and 0.877, representing higher values than 0.70 (Gursoy et al., 2019)\. In addition, the Cronbach's value of the entire sample date was 0.927, meaning it portrayed noble reliability for the assessment of the variables (Lee & Wu, 2017). Conversely, during the validity analysis, the Bartlett spherical test and KMO test were used first, and the final data was computed. According to the data, the Bartlett spherical test level indicated a significant value of $p<0.001$, which reflected that the sample data was suitable for factor analysis, and the KMO value was 0.994, more extensive than 0.9, which reflected a suitable factor analysis (Wu et al., 2014). In addition, after using the SPSS 25.0 to analyze the data, all the factor loads items on their latent variables were assessed through the factor analysis (Hair Jr. et al., 2017). According to the results, all the factor loads had a value of more than 0.70, and each latent variable's average variance extracted value (AVE) was more than 0.50. This reflects that the evaluation of variables portrayed an excellent convergence (Hair Jr. et al., 2017).

Table 2
Reliability and validity analysis

Latent variable	Items	Factor load	Cronbach's value	Composite reliability	AVE
AC	AC1	0.813			
	AC2	0.823	0.743	0.855	0.662
	AC3	0.805			
IS	IS1	0.836			
	IS2	0.815	0.751	0.858	0.668
	IS3	0.800			
IT	IT1	0.836			
	IT2	0.800	0.773	0.860	0.672
	IT3	0.824			
UV	UV1	0.785			
	UV2	0.701			
	UV3	0.777	0.816	0.874	0.581
	UV4	0.766			
	UV5	0.779			
HV	HV1	0.748			
	HV2	0.711			
	HV3	0.790	0.836	0.877	0.588
	HV4	0.788			
	HV5	0.794			
CPI	CPI1	0.759	0.788	0.864	0.615
	CPI2	0.809			
	CPI3	0.832			
	CPI4	0.733			

4.2 Deviation test

To reduce the standard method deviation test, the scholars obscured the latent variable names in the questionnaire design process and incorporated the Harman single-factor analysis integrated by various studies (Hair Jr. et al., 2017). Furthermore, without any rotation, the items in the questionnaire were analyzed by the factor analysis, and the highest demonstrated factor variance contribution rate was 38.86 per cent. The study concludes that the standard deviation test was not significant from the above analysis (Henseler, 2017).

4.3 Hypothesis tests results

The scholars used the Amos23.0 software to construct an SEM model for fitting during the study (Henseler, 2017). Based on the model fitting results, the effect of the model was moderately good (CMIN= 3.769, AGFI=0.868, NFI=0.867, IFI=0.899, RMESA = 0.066, and CFI=0.898). Therefore, these results indicated that the recommended model fitting was appropriate for advanced path analysis (Henseler, 2017).

The table below shows the hypothesis results where the p=value is less than 0.001, indicating that all the variable relationships are significant.

Table 3
Hypothesis results

Hypotheses	Path	Estimate	S.E.	C.R.	p	Result
H1a	AC→UV	0.312	0.041	7.636	***	supported
H1b	AC→HV	0.229	0.045	5.106	***	supported
H1c	IS→UV	0.547	0.049	11.233	***	supported
H1d	IS→HV	0.560	0.054	10.304	***	supported
H1e	IT→UV	0.287	0.032	9.073	***	supported
H1f	IT→HV	0.296	0.037	8.095	***	supported
H2a	UV→CPI	0.229	0.062	3.693	***	supported
H2b	HV→CPI	0.605	0.064	9.429	***	supported

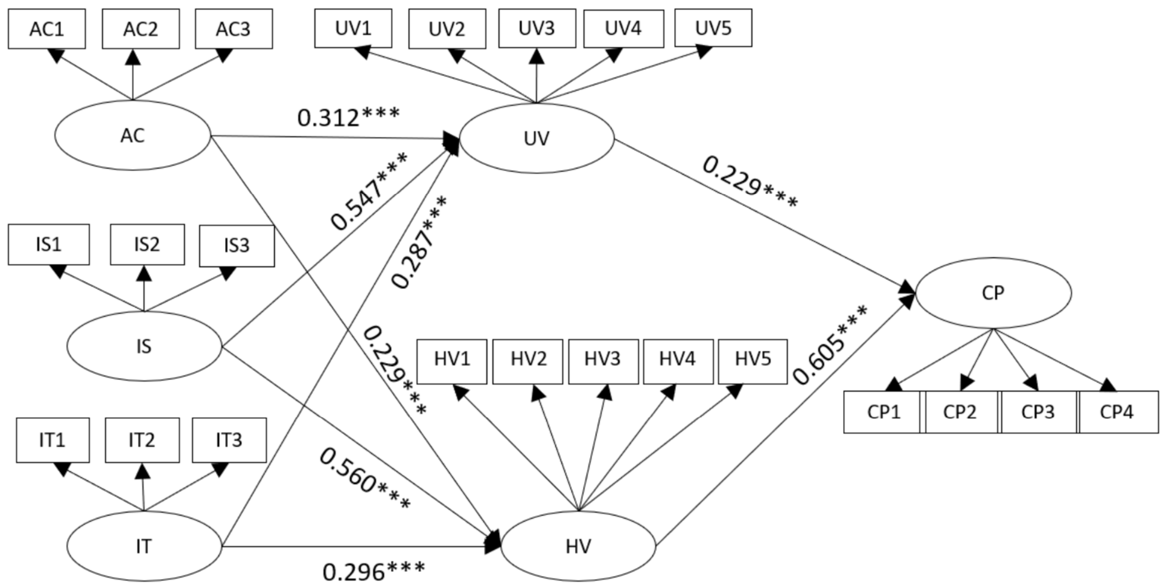

Fig. 2. Model and the path coefficient (P< 0.001)

According to the results, Hypothesis 1a and 1b show a significant test, meaning that the accuracy of Artificial Intelligence machinery experience of consumers' online errands platforms is favorable to enhance the customers' perceived hedonic and utilitarian value (Kazakeviciute & Banyte, 2012). In addition, with an increase in accuracy of the Artificial Intelligence technology, customers are more likely to achieve the perceived hedonic and utility value in purchasing. Comparatively, Hypothesis 1c and 1d passed the significance level, reflecting that AI technology's insight experience increases the customers' sensitivity to hedonic and utilitarian values (Hair Jr. et al., 2017). Furthermore, hypotheses 1e and 1f did pass the significance test, meaning that the robust the online interaction of the AI technology, the more favorable to escalates customers' opinion of perceived hedonic and utilitarian value. Results show that both Hypothesis 2a and 2b passed the significance test. This means that the perceived hedonic and utilitarian value integrated with Artificial Intelligence technology can enhance the creation of the customer's purchase intention (Kazakeviciute & Banyte, 2012).

4.4 Discussions

According to the study results and findings, incorporating AI technology in business online shopping platforms provides a favorable atmosphere for perceived consumers' behaviors (Lee & Wu, 2017). The study reveals that the more accurate the AI technology is, the more it will provide a conducive platform for customers' perceived hedonic and utilitarian values. Also, as reflected from the survey outcomes, customers tend to be satisfied with text retrieval facilitated by AI technology systems but less influenced n by voice and image recognition technology. The accuracy produced by both concepts affects the recovery experience of many customers (Lee & Wu, 2017). Conversely, the perceived utility value of the Artificial Intelligence business technology enhanced by the accuracy is higher than the perceived hedonic value. This means that customers anticipate that AI technology produces higher utility in shopping time, cost-saving, and convenience. However, the insight of the perceived hedonic value generated by accuracy is not intense as that of perceived utilitarian value (Lee & Wu, 2017).

Additionally, the AI technology provides more significant insights to the online shopping consumers, which does not improve the customers' perceived utilitarianism but also encourages pleasure in the purchasing process through curiosity, desire, interest, and the consumptions process (Luo et al., 2019). Also, the customers' purchase intention by the perceived hedonic value is likely to be more intense than the perceived utilitarian value (Luo et al., 2019). The study reveals that the higher the contact of AI technology on an online enterprises the more favorable the generation of customers' enjoyment and perceived utilitarian value. In addition, consumers agree that the Artificial Intelligence virtual assistant's satisfaction is less compared to insight and accuracy satisfaction. Similarly, the interactive experience of Artificial Intelligence technology on online shopping platforms tends to be weak in encouraging the formation of the two perceived values (Luo et al., 2019).

4.5 The Significance of the Results

According to the study results, the academic and empirical significance of this research in the field of Artificial Intelligence in Jordan and other places and the current analysis of this technology's application on e-commerce platforms is still inadequate (Kazakeviciute & Banyte, 2012). However, the exploration of this study in the field of AI tends to fill the gaps. In addition, this research provides the primary data and information that other scholars can use to conduct future research concerning AI and other consumer behaviors. Therefore, the results show that this study is reliable to advance AI research in the future. Another significance of this study is that it expands the application of the Structural Equation Model (SEM) and SOR model through the experience reflected by Artificial Intelligent as a stimulus variable, performance of customers, and the purchasing intention via perceived value which acts as a mediating mechanism (Kazakeviciute & Banyte, 2012). In this case, the results validate that the perceived hedonic and utility value portrays significant mediating impacts. Additionally, the study validates the three experiences (insight, accuracy, and interactive) of the AI technology with different paths of perceived hedonic and utilitarian values. It concludes that the perceived utility value of the three experiences is significantly greater than the perceived utility value (Kazakeviciute & Banyte, 2012).

4.6 Limitation of the Study

The scholars only evaluated the core perceived value (hedonic and utilitarian) that influences the internal consumers' mechanism as the intermediary effect during the study. However, the study failed to consider other internal factors such as consumers' attitudes, perceived risks, flow experience, taste, and preferences that affect the consumers' behaviors (Chiu et al., 2014).

5. Conclusion

In conclusion, the perceived hedonic and utilitarian values play a significant role in the consumers' purchase intention and AI technology which shows that the AI technology can alter the purchasing behaviors by mediating the perceived values (Chiu et al., 2014). In addition, as reflected by the study, the promotion of perceived hedonic value in customers' online shopping seems to be greater than the perceived utility value. Again with the intense use of AI marketing technology in modern online shopping enterprises, various functional necessities such as shopping efficiency, convenience, and product selection have become a routine mainstream in e-commerce grounds (Chiu et al., 2014). In this case, the consumers do not have value-added emotions, thus making perceived utility show minor differences. Consumers are more likely to prefer the spiritual experience of pleasure, relaxation, and stimulation of purchasing desire generated by AI technology in the global platform of online shops. Artificial Intelligence is dynamic and frequently changing its trajectory relevant to customers' behavior, endlessly gaining potential demands and motivating customers' shopping interests (Chiu et al., 2014).

According to the study, incorporating Artificial Intelligence technology in online shopping platforms does not directly encourage the customers' purchasing behaviors, as the hedonic and utilitarian values are efficient mediators (Gan & Wang, 2017). Similarly, AI technology is currently used to help online enterprise to promote their shopping strategy but cannot work directly. This means that it is just an online platform for shopping; however, consumers must find emotional feelings to arouse their instincts to like all products and services valuable to them (Gan & Wang, 2017). For example, the price and experience may change their behaviors and purchase intentions. In this study, perceived hedonic and utility values show a clear connection between the Artificial Intelligence technology experience and the customers' buying intention on online e-commerce enterprises or platforms (Gan & Wang, 2017).

6. Recommendation

First, online shopping businesses should consider the technological effects of Artificial Intelligence on customers' perceived hedonic cognition and extend their usage boundary based on the customers' online shopping behaviors (Lee & Wu, 2017). Similarly, they should expand their combination of artificial networks, machine vision, and other innovations while exploring customers' psychological behaviors. Although few empirical pieces of research demonstrate the effects or influence of AI technology on consumers purchasing behaviors, further studies need to be conducted in the future to examine the impacts of AI on other factors. For example, further research is necessary to evaluate how AI influences the quality of goods produced and distributed, which may directly or indirectly affect consumers' consumption (Davenport et al, 2020). Also, the scholars conducted the study in a developed area where the technology is advanced. However, the researcher should consider conducting a study in less developed areas where the technology is not well advanced to compare the results. Also, the AI technology does not work directly with consumers; there must be perceived mediators to trigger the emotional stimulus of the customer.

Since different consumers think differently due to their cognitive features, researchers should conduct research using different respondents in different geographical areas (Davenport et al, 2020).

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References

Al Adwan, A., Aladwan, K. M., & Al-Adwan, A. S. (2019). E-marketing strategic for Jordanian small business to increase sale in local e-market. *Academy of Strategic Management Journal*, *18*(6), 1-13.

Adwan, A. A. (2020). The impact of social media on consumer awareness towards buying copy brand. *International Journal of Electronic Marketing and Retailing*, *11*(2), 199-215.

Al-Adwan, A. S., Kokash, H., Adwan, A. A., Alhorani, A., & Yaseen, H. (2020). Building customer loyalty in online shopping: the role of online trust, online satisfaction and electronic word of mouth. *International Journal of Electronic Marketing and Retailing*, *11*(3), 278-306.

Al Adwan, A., Zamil, A. M., & Areiqat, A. Y. (2021). FACTORS AFFECTING ONLINE SHOPPING BEHAVIOR OF CONSUMERS UNDERSTANDING FACTORS LEADING TO CONSUMERS'LOYALTY. *Academy of Strategic Management Journal*, *20*, 1-8.

Al Adwan, A., Zamil, A. M., & Areiqat, A. Y. (2021). SOCIAL MEDIA'S IMPACT ON BUSINESS & COMMUNITY. *Academy of Strategic Management Journal*, *20*, 1-5.

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W... & Yang, H. (2018). Consumer choice and autonomy in the age of artificial intelligence and big data. *Customer needs and solutions*, *5*(1), 28-37.

Avcilar, M. Y., & Özsoy, T. (2015). Determining the effects of perceived utilitarian and hedonic value on online shopping intentions. *International Journal of Marketing Studies*, *7*, 27-49.

Bock, D. E., Wolter, J. S., & Ferrell, O. C. (2020). Artificial intelligence: disrupting what we know about services. *Journal of Services Marketing*, *34*(3), 317-334.

Bundorf, K., Polyakova, M., & Tai-Seale, M. (2019). *How do humans interact with algorithms? Experimental evidence from health insurance* (No. w25976). National Bureau of Economic Research.

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. *Industrial Management & Data Systems*.

Chiu, C. M., Wang, E. T., Fang, Y. H., & Huang, H. Y. (2014). Understanding customers' repeat purchase intentions in B2C e-commerce: the roles of utilitarian value, hedonic value and perceived risk. *Information Systems Journal*, *24*(1), 85-114.

Chang, H. J., Eckman, M., & Yan, R. N. (2011). Application of the Stimulus-Organism-Response model to the retail environment: the role of hedonic motivation in impulse buying behavior. *The International Review of Retail, Distribution and Consumer Research*, *21*(3), 233-249.

Cheung, M. W. L. (2015). metaSEM: An R package for meta-analysis using structural equation modeling. *Frontiers in psychology*, *5*, 1521.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*(1), 24-42.

Gan, C., & Wang, W. (2017). The influence of perceived value on purchase intention in social commerce context. *Internet Research*.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumer's acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, *49*, 157-169.

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, *49*(1), 30-50.

Henseler, J. (2017). Bridging design and behavioral research with variance-based structural equation modeling. *Journal of advertising*, *46*(1), 178-192.

Hair Jr, J. F., Babin, B. J., & Krey, N. (2017). Covariance-based structural equation modeling in the Journal of Advertising: Review and recommendations. *Journal of Advertising*, *46*(1), 163-177.

Islam, J. U., & Rahman, Z. (2017). The impact of online brand community characteristics on customer engagement: An application of Stimulus-Organism-Response paradigm. *Telematics and Informatics*, *34*(4), 96-109.

Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review*, *61*(4), 135-155.

Kietzmann, J., Paschen, J., & Treen, E. (2018). Artificial intelligence in advertising: How marketers can leverage artificial intelligence along the consumer journey. *Journal of Advertising Research*, *58*(3), 263-267.

Kim, J., & Lennon, S. J. (2013). Effects of reputation and website quality on online consumers' emotion, perceived risk and purchase intention: Based on the stimulus-organism-response model. *Journal of Research in Interactive Marketing*.

Kazakeviciute, A., & Banyte, J. (2012). The relationship of consumers 'perceived hedonic value and behavior. *Engineering Economics*, *23*(5), 532-540.

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science*, *38*(6), 937-947.

Lee, C. H., & Wu, J. J. (2017). Consumer online flow experience: The relationship between utilitarian and hedonic value, satisfaction and unplanned purchase. *Industrial Management & Data Systems*, *117*(10), 2452-2467.

Meske, C., Wilms, K., & Stieglitz, S. (2019). Enterprise social networks as digital infrastructures-understanding the utilitarian value of social media at the workplace. *Information Systems Management*, *36*(4), 350-367.

Wu, W. Y., Lee, C. L., Fu, C. S., & Wang, H. C. (2014). How can online store layout design and atmosphere influence consumer shopping intention on a website?. *International Journal of Retail & Distribution Management*, *42*(1), 4-24.