Study on the mechanism of non-immersive VR technology's impact on consumer decision-making

——Take high-intervention goods for example

Lan Li

School of Management, Hankou University, Wuhan, China

1292731581@qq.com

Abstract. This study explores the impact of non-immersive VR in online real estate platforms on commodity consumption decisions. Non-immersive VR displays simulated environments on screens, with users interacting via keyboard and mouse. BEKE, a prominent Chinese real estate platform, introduced VR house-viewing in 2018, marking its the first user of this technology in e-commerce. This study deeply analyzes the effect of non-immersive VR on consumer decision time, using survival model, tendency matching, and Hecmann control function, to reveal its role in decision-making. The study aims to provide useful insights for the innovative development of the online real estate industry.

Keywords: Non-immersive VR;Consumer decision;High intervention goods;Digital marketing.

1. Introduction

Due to high equipment costs, immersive virtual reality is currently limited to high-end fields like medical, construction, and military. In contrast, non-immersive VR is more accessible, displaying the virtual environment on a computer screen and enabling interaction via keyboard and mouse, making it popular in business.

Recently, non-immersive VR has gained traction in real estate. This technology lets buyers view properties online, saving time and effort. Platforms like Zillow and BEKE offer such features, enhancing purchase decision efficiency and accuracy.

Real estate as a high-intervention industry with high commodity value, benefits greatly from non-immersive VR. However, empirical studies on non-immersive VR technology's impact on high-intervention products are scarce. Past studies mostly focused on low-intervention items like consumer goods. Therefore, further exploring non-immersive VR technology's influence on high-intervention product consumption decisions is crucial for promoting its use in real estate.

2. Methods

The The data of this study takes housing properties, marketing start and end time as the core content, and constitutes a typical "time-event" type data set. In view of the characteristics of such data, this study comprehensively uses two survival analysis methods, accelerated failure time model and Cox proportional risk model, aiming to deeply analyze the survival status and risk level of individuals.

Specifically, this study first uses the accelerated failure time model to reveal the specific impact of virtual reality house viewing technology on consumption decision time. The model takes the survival rate S at time t as the dependent variable to explore the potential role of the house viewing factors on the house sales process of the VR by fitting a function of a series of variable X. Under the framework of this study, survival refers specifically to the overall proportion of homes that had not been sold at the time of data collection. The functional form of the accelerated failure time model is as follows:

Logs (presence time i)=β o+β1(virtual reality)+β2Total price i+β c(controlled variable i)+ε i (2.1)

Where the value of $\beta_1$represents the role of virtual reality on decision consumption time. If the $\beta_1$is significantly negative, it indicates that virtual reality house viewing technology can reduce the existence time of houses to accelerate consumption decisions.

Secondly, this paper also uses the Cox proportional risk model to explore the impact of virtual reality on consumption decision time. The risk rate of the house in this paper λ refers to the probability that the house is sold at time t. The proportional hazards model is presented as follows:

$\lambda(t |Xi)=\lambda_0(t)\exp(\alpha0+\alpha1$virtual reality i $+\alpha2$Total price i$+\alpha$ c(controlled variable i) (2.2)

In the proportional hazards model, the parameter α in this paper α1 For the use of the risk rate of the sale of virtual reality. Thus, if the α1 significantly positive effect suggests that virtual reality accelerates the marketing process of homes, making them easier to sell.

3. Results

3.1 Impact of non-immersive VR on consumer decision-making process

In the decision-making process of consumers, the association between housing price and objective quality has a significant impact on the purchase intention. Objective quality, as an unbiased estimate of the commodity quality of product attributes based on detailed evaluation, represents the fair value of the goods, while the selling price reflects its market value. When homes sell for significantly less than their objective quality, consumers often show a higher willingness to buy.

As shown in column (1) of Table 3.1, the coefficient of virtual reality is significantly positive, with a specific value of 0.545. This result shows that the use of non-immersive virtual reality technology can significantly increase the flow of the home details page. This indicates that VR, as an effective information cue can increase the likelihood of consumers conducting detailed evaluation during the user information collection stage. As a result, virtual reality have higher page views than homes that do not use virtual reality.

In addition, as shown in column (2) of Table 3.1, the coefficient of virtual reality is also significantly positive, with a value of 0.560. The results show that houses that support virtual reality house viewing are easier to be added to the consumer attention list when consumers make a detailed assessment of house properties. This suggests that non-immersive virtual reality technology can enhance consumers' willingness to see homes offline. Therefore, after users evaluate the alternative options, the homes that support virtual reality have a higher amount of attention than those that do not support this feature.

Table 3.1 Impact of non-immersive VR on consumer decision-making process

	(1) Page access	(2) Follow with interest
Virtual reality	0.545*** (0.0265)	0.560*** (0.0412)
Total price	0.083*** (0.0185)	-0.037* (0.0223)
No price adjustment	-0.335*** (0.0283)	-0.170*** (0.0343)
Area	-0.002* (0.0010)	-0.006*** (0.0014)
Building age	-0.001 (0.0013)	0.000 (0.0030)
Picture		0.067*** (0.0049)
Existence time	0.010*** (0.0002)	0.002*** (0.0002)

Constant term	7.680*** (0.6737)	0.119*** (0.0216)
Sample capacity	19767	19767
False R^2	0.040	0.171
Category variable	yes	yes
On the shelf month	yes	yes

Note: Because both page visits and attention are the amount of accumulation of the house in the whole marketing process, there are time variables that are controlled in the model. Shown in parentheses are the robust standard deviations.*p<0.10，**p<0.05，***p<0.01。

3.2 Impact of non-immersive VR on consumer transformation

This paper uses a two-stage linear model and a propensity post-matching sample to explore the impact of virtual reality on consumer conversion, and the results are shown in Table 3.2.

Table 3.2 Impact of non-immersive VR on consumer transformation

	(1)	(2)	(3)	(4)
	Control is not adjusted		Unadjusted house	
	Conversion rate	The conversion advantage rate	Conversion rate	The conversion advantage rate
Virtual reality	0.001*	0.002*	0.003***	0.004***
	(0.0005)	(0.0009)	(0.0009)	(0.0012)
Total price	-0.001* (0.0004)	-0.001** (0.0006)	0.001 (0.0008)	0.000 (0.0011)
No price adjustment	0.010***	0.013***		
	(0.0006)	(0.0009)		
Area	-0.000*** (0.0000)	-0.000*** (0.0000)	-0.000*** (0.0000)	-0.000*** (0.0001)
Building age	-0.000 (0.0000)	-0.000 (0.0001)	-0.000 (0.0001)	-0.000* (0.0001)
Picture	-0.000* (0.0001)	-0.000** (0.0002)	-0.000** (0.0002)	-0.001* (0.0003)
Constant term	0.033(0.0059)	0.036*** (0.0069)	0.044*** (0.0096)	0.050*** (0.0119)
Sample capacity	19767	19763	7589	7587
R^2	0.240	0.139	0.294	0.188
Category variable	yes	yes	yes	yes
On the shelf month	yes	yes	yes	yes

Note: Steady standard deviation is shown in parentheses.*p<0.10，**p<0.05，***p<0.01.

In Table 3.2, columns (1) and (2). This method effectively deals with the endogenous problem caused by the difference between the price and the objective quality. In addition, columns (3) and (4) show the regression results matched based only on the unadjusted samples, further eliminating the impact of price endogeneity. In Table 3.2, columns (1) and (3) set conversion rates as dependent variables, while columns (2) and (4) include conversion odds as dependent variables.

It is noteworthy that the coefficients about VR showed a significant positive effect in all columns. This result suggests that homes that support VR viewing are more likely to attract consumer attention. This significant positive effect is not only derived from the increase in page

views brought about by virtual reality technology, but also from the richer detailed information that consumers get through virtual reality house viewing when evaluating alternatives. These findings fully demonstrate that the detailed information provided by the virtual reality house viewing function can effectively assist consumers to distinguish between the quality of the housing.

In conclusion, after consumers' housing quality assessment, houses that support VR have higher conversion rates and higher conversion advantages compared with those that do not support this function. This discovery profoundly reveals the internal mechanism of virtual reality house viewing function in the process of accelerating consumption decision-making.

4. Conclusion

This paper investigates how non-immersive VR house viewing affects the duration of housing marketing using a survival model. VR is critical in mitigating uncertainties about housing quality before purchase. It plays a pivotal role in consumer decision-making, affecting information gathering and alternative assessment.

The research finds that VR house viewing effectively expedites the housing marketing process. VR integration increases page visits to detailed home listings during information gathering. Homes offering VR viewing are more likely to be considered by consumers during alternative evaluation. VR also enhances conversion rates and conversion advantage rates between information collection and alternative evaluation stages.

These findings provide empirical support and theoretical rationales for understanding visual elements' operational mechanisms in e-commerce. They offer valuable insights and recommendations to practitioners on optimizing visual element presentation on web pages.

References

[1] Wang,M,Li,XandChau,P.Y.K.2020."Leveraging Image-Processing Techniques for Empirical Research:Feasibility and Reliability in Online Shopping Context,"Information Systems Frontiers,1-20.

[2] You,Q,Jin,H,Wang,Z,Fang.C.,and Luo,J.2016.“Image Captioning with Semantic Attention,”in Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition,4651-4659

[3] Sun Puyang, Zhang Jinjia, Jiang Xiaoyu.2017. "E-commerce, search for cost and consumer price change," Economic Research (52:7), 139-154.

[4] Han Jinxing, Zhang Zhe, Gu Chenyan.2016. "The impact of consumer social interaction on group-buying trust in online group-buying," Management Review (9), 148-162.

[5] Steffen, J.H, Gaskin,J.E, Meservy, T.O, Jenkins,J.L, and Wolman,I. 2019. "Framework of Affordances for Virtual Reality and Augmented Reality," Journal of Management Information Systems (36:3),683-729

[6] Yan,Z, Wu,Q, and Li,X.2016.“Do Hirsch-Type Indices Behave the Same in Assessing Single Publications? An Empirical Study of 29 Bibliometric Indicators," Scientometrics (109:3),1815-1833.

[7] Wang.Y,and Chaudhry,A.2018.“When and How Managers Responses to Online Reviews Affect Subsequent Reviews,"Journal of Marketing Research(55:2),163-177.

[8] Zhang,M,and Luo,L.2019.“Can User-Posted Photos Serve as a Leading Indication of Restaurant Survival?Evidence from Yelp,”Working Paper.

[9] Zhang,S,Lee,D,Singh,P.V,and Srinivasan,K.2017.“How Much Is an Image Worth?Airbnb Property Demand Analytic Leveraging A Scalable Image Classification Algorithm,”SSRN Electronic,Journal.

[10] Ych,C.H,Wang,Y.S,Li,H.T,and Lin,S.Y.2017.“The Effect of Information Presentation Modes on Tourists' Responses in Internet Marketing:The Moderating Role of Emotions,"Journal of Travel and Tourism Marketing(34:8),1018-1032.