"IMPACT OF AUGMENTED REALITY ON CONSUMER PURCHASE INTENTIONS AND ADOPTION IN RETAIL SECTOR"

PhD Synopsis

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1. Abstract

The retail sector is undergoing a profound transformation driven by digital technologies, with Augmented Reality (AR) emerging as a pivotal tool for enhancing the consumer experience. Here, the researcher examines the impact of AR technology on consumer purchase intentions and its adoption within the retail landscape. By overlaying digital information onto the physical environment, AR mitigates key online and offline purchasing barriers, such as the inability to evaluate products physically (e.g., trying on clothes or visualizing furniture in a home) and information asymmetry. The research synthesizes findings from recent empirical studies to argue that AR features—such as virtual try-ons, 3D product previews, and interactive in-store navigation—significantly enhance consumer engagement, increase perceived vividness and telepresence, and reduce perceived risk. These factors collectively lead to higher levels of consumer confidence and more informed decision-making, thereby positively influencing purchase intentions and reducing return rates. Furthermore, the adoption of AR in retail is influenced by factors including technology acceptance variables (e.g., perceived usefulness and

ease of use), consumer innovativeness, and the quality of the AR experience itself. Despite its potential, challenges to widespread adoption remain, including technological limitations, development costs, and privacy concerns. This study concludes that AR represents a strategic imperative for retailers seeking to gain a competitive advantage, foster deeper brand connections, and drive sales in an increasingly omnichannel world.

2. Brief description of the state of the research topic

Augmented Reality (AR) technology, which overlays digital content onto the real world, has seen gradual but significant growth in India over the past decade. While AR gained global prominence in the early 2010s with applications like Pokémon Go, its adoption in India began later due to infrastructural and technological challenges. However, with increasing smartphone penetration and affordable internet, India has emerged as a promising market for AR innovations. Early experiments in AR were primarily seen in advertising and entertainment, with brands leveraging the technology for interactive campaigns (Kumar & Sharma, 2018).

Here Researcher addresses a critical challenge in modern retail: the gap between online shopping convenience and the inability to physically evaluate products. The primary objective is to empirically investigate how Augmented Reality (AR) technology bridges this gap by influencing consumer psychology and behavior, thereby increasing purchase intentions. A secondary objective is to identify the key drivers and barriers influencing the adoption of this technology by retailers. The study employs a Quantitative method approach: A structured online survey was administered to a sample of consumers who interacted with a branded AR experience. Data was analysed using statistical methods (Structural Equation Modelling) to test hypotheses linking AR Factors like Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Behavioural Intention and Usage Behaviour.

3. Statement of the Problem

Despite growing investments in AR by major retailers like Amazon, IKEA, and Sephora, consumer adoption rates vary significantly across demographics. Younger, tech-savvy shoppers show higher engagement with AR tools, whereas older or less digitally literate consumers remain hesitant due to usability concerns (Yim et al., 2024). Additionally, while studies suggest that AR reduces product return rates by improving purchase confidence (Hilken et al., 2022), there is conflicting evidence on whether these benefits translate into sustained sales growth or merely serve as short-term novelty attractions. Furthermore, the role of cultural and economic differences in shaping AR adoption is particularly relevant in emerging markets like India, where smartphone penetration is high, but digital literacy and infrastructure challenges persist (NASSCOM, 2024).

This study seeks to address these gaps by investigating:

1. **How AR influences consumer purchase intentions**—Does AR-driven interactivity increase conversion rates, or does it lead to decision paralysis due to excessive customization options?
2. **Barriers to AR adoption in retail**—What factors (technological, psychological, or infrastructural) hinder widespread consumer acceptance?
3. **The long-term viability of AR in retail**—Are AR-enhanced shopping experiences sustainable, or will diminishing novelty effects reduce engagement over time?

By analyzing consumer behavior data, retailer case studies, and adoption trends, this research aims to provide actionable insights for businesses seeking to integrate AR effectively while identifying strategies to overcome adoption barriers.

4. Research Gap & Research Objective

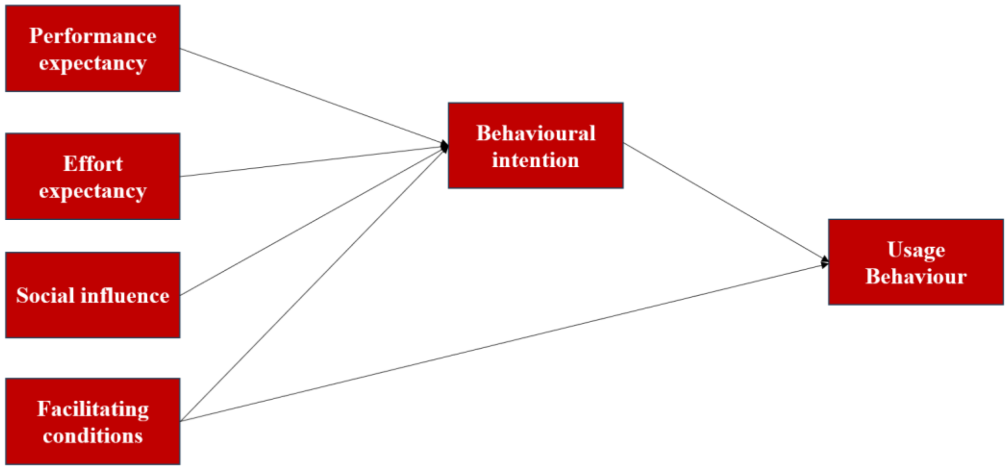
Bases	Research Gap	Why it Matters?	Research Objective
Long-Term Effects of AR on Consumer Behavior	Most studies focus on short-term purchase intentions rather than long-term brand loyalty or repeat purchases.	AR may initially attract customers, but does it sustain engagement over time?	To examine the long-term effects of AR on brand loyalty and repeat purchase behavior in retail.
Privacy Concerns	Few studies explore how data privacy fears (e.g., facial recognition in AR try-ons) affect adoption.	consumers may avoid AR if they perceive invasive data collection.	To investigate the impact of privacy concerns (e.g., data tracking in AR apps) on consumer trust and AR adoption intentions.

AR Adoption in SMEs	Most studies examine AR in big brands (e.g., Nike, Sephora), ignoring SMEs with limited budgets.	SMEs need cost-effective AR strategies to compete.	To explore barriers and cost-effective AR solutions for small and medium-sized retailers in emerging economies.
AR in Offline vs. Online Retail	Most research focuses on e-commerce AR (e.g., virtual try-ons), neglecting in-store AR (e.g., smart mirrors, AR navigation).	Physical retail may benefit differently from AR than online platforms.	To compare the effectiveness of AR in enhancing purchase intentions for brick-and-mortar stores versus e-commerce platforms.

5. Conceptual framework

The conceptual model depicted in the image is based on the Unified Theory of Acceptance and Use of Technology (UTAUT), which integrates elements from several earlier technology acceptance theories. Here's a brief explanation of the model with references:

1. Performance Expectancy: Refers to the degree to which an individual believes that using a technology will help them achieve gains in job performance (Venkatesh et al., 2003).
2. Effort Expectancy: The ease of use associated with the technology (Venkatesh et al., 2003).
3. Social Influence: The extent to which individuals perceive that important others (e.g., peers, supervisors) believe they should use the technology (Venkatesh et al., 2003).
4. Facilitating Conditions: The degree to which an individual believes that organizational and technical infrastructure exists to support the use of the technology (Venkatesh et al., 2003).
5. Behavioural Intention: The individual's intention to use the technology, influenced by the above factors (Davis, 1989; Venkatesh et al., 2003).
6. Usage Behaviour: The actual use of the technology, driven by behavioural intention and facilitating conditions (Venkatesh et al., 2003).



6. Research Methodology

<u>RESEARCH QUESTIONS</u>

1. How does prolonged exposure to AR shopping tools influence brand loyalty and repeat purchase behavior?
2. To what extent do privacy concerns (e.g., facial data collection in AR try-ons) hinder consumer adoption of AR retail tools?
3. How can retailers balance AR personaliza Data Collection Metho tion with ethical data usage to build consumer trust?
4. How does the impact of AR on purchase intentions differ between physical stores (e.g., AR mirrors) and e-commerce platforms (e.g., virtual try-ons)?
5. What are the primary barriers preventing small retailers from adopting AR, and how can they be addressed cost-effectively?
6. How do Performance expectancy, effort expectancy, social influence, facilitating condition, behavioural intentions and usage behaviour impact the online buying behaviour of shoppers?

7. Research Hypothesis

Independent sample T test- Gender

H1: there is significance difference between various categories of age with respect to performance expectancy.

H2: there is significance difference between various categories of age with respect to effort expectancy.

H3: there is significance difference between various categories of age with respect to social influence.

H4: there is significance difference between various categories of age with respect to facilitating conditions.

H5: there is significance difference between various categories of age with respect to behavioural intentions.

H6: there is significance difference between various categories of age with respect to usage behaviour

Independent sample T test-Marital Status

H7: There is a significance difference between Single and married regarding performance expectancy.

H8: There is a significance difference between Single and Married regarding effort expectancy.

H9: There is a significance difference between Single and Married regarding social influence.

H10:There is a significance difference between Single and Married regarding facilitating conditions.

H11: There is a significance difference between Single and Married regarding behavioural intentions.

H12: There is a significance difference between Single and Married regarding usage behaviour.

ANOVA- Age wise

H13: there is significance difference between various categories of age with respect to performance expectancy.

H14: there is significance difference between various categories of age with respect to effort expectancy.

H15: there is significance difference between various categories of age with respect to social influence.

H16: there is significance difference between various categories of age with respect to facilitating conditions.

H17: there is significance difference between various categories of age with respect to behavioural intentions.

H18: there is significance difference between various categories of age with respect to usage behaviour.

ANOVA- Occupation wise

H19: There is significant difference between various occupation categories with respect to performance expectancy.

H20: There is significance difference between various occupation categories with respect to effort expectancy.

H21: There is significance difference between various occupation categories with respect to social influence.

H22: There is significance difference between various occupation categories with respect to facilitating conditions.

H23: There is significance difference between various occupation categories with respect to behavioural intentions.

H24: There is significance difference between various occupation categories with respect to usage behaviour.

ANOVA- Education wise

H25: There is significant difference between various education categories with respect to performance expectancy.

H26: There is significance difference between various education categories with respect to effort expectancy.

H27: There is significance difference between various education categories with respect to social influence.

H28; There is significance difference between various education categories with respect to facilitating conditions.

H29: There is significance difference between various education categories with respect to behavioural intentions.

H30: There is significance difference between various education categories with respect to usage behaviour

Monthly Income wise ANOVA

H31: There is significant difference between various Monthly Income categories with respect to performance expectancy.

H32: there is significance difference between various Monthly Income categories with respect to effort expectancy.

H33: there is significance difference between various Monthly Income categories with respect to social influence.

H34: there is significance difference between various Monthly Income categories with respect to facilitating conditions.

H35: there is significance difference between various Monthly Income categories with respect to behavioural intentions.

H36: there is significance difference between various Monthly Income categories with respect to usage behaviour.

Structural Model Assessment using Path Analysis

H37: There is a positive effect of Performance Expectancy on Behavioural Intention.

H38: There is a positive effect of Effort Expectancy on Behavioural Intention.

H39: There is Positive effect of Social Influence on Behavioural Intention.

H40: There is Positive effect of Facilitating Conditions on Behavioural Intention.

H41: There is Positive effect of Facilitating Conditions on Usage Behaviour.

H42: There is Positive effect of Behavioural Intention on Usage Behavior.

Path analysis of mediating variables

H43: There is positive mediating effect between effort expectancy, behavioural intentions and usage behavior.

H44: There is positive mediating effect between facilitating condition, behavioural intentions and usage behavior.

H45: There is positive mediating effect between performance expectancy,behavioural intentions and usage behavior.

H46: There is positive mediating effect between Social Influence, behavioural intentions and usage behavior.

8. Key results and analysis

Independent sample T test-Gender

	Levene's Test for Equality	t-test for Equality of Means

		of Variances								
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
PE	Equal variances assumed	2.145	.143	-.845	901	.398	-.26457	.31295	-.87876	.34961
	Equal variances not assumed			-.843	883.635	.399	-.26457	.31372	-.88029	.35114
EE	Equal variances assumed	3.036	.082	-1.016	901	.310	-.33052	.32534	-.96904	.30800
	Equal variances not assumed			-1.013	882.132	.311	-.33052	.32622	-.97077	.30973
SI	Equal variances assumed	2.004	.157	-1.346	901	.179	-.25399	.18869	-.62432	.11633

	Equal variances not assumed			-1.340	866.205	.181	-.25399	.18958	-.62608	.11809
FC	Equal variances assumed	3.248	.072	-1.323	901	.186	-.42760	.32309	-1.06170	.20650
	Equal variances not assumed			-1.318	869.777	.188	-.42760	.32448	-1.06445	.20924
BI	Equal variances assumed	2.645	.104	-1.234	901	.217	-.32613	.26425	-.84475	.19250
	Equal variances not assumed			-1.229	872.365	.219	-.32613	.26531	-.84684	.19458
UB	Equal variances assumed	3.277	.071	-1.380	901	.168	-.32411	.23492	-.78515	.13694

	Equal variances not assumed			-1.373	863.225	.170	-.32411	.23609	-.78749	.13928

An independent-samples t-test was conducted to compare the performance expectancy, Effort Expectancy, social influence, facilitation condition, behavioural intention & usage behaviour for males and females. first, assumptions of normality and leven's test were checked. Both the assumptions are met. There was no significant difference in age As p value is greater than 0.05, so the null hypothesis is accepted.

Independent sample T test-Marital Status

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
PE	Equal variances assumed	.590	.443	.250	901	.803	.07915	.31641	-.54183	.70013
	Equal variances not assumed			.249	809.965	.803	.07915	.31797	-.54500	.70330

EE	Equal variances assumed	1.098	.295	.452	901	.651	.14877	.32897	-.49687	.79441
	Equal variances not assumed			.449	803.491	.653	.14877	.33127	-.50148	.79902
SI	Equal variances assumed	.591	.442	.630	901	.529	.12020	.19086	-.25438	.49478
	Equal variances not assumed			.624	797.154	.533	.12020	.19256	-.25779	.49818
FC	Equal variances assumed	.798	.372	.633	901	.527	.20681	.32679	-.43455	.84817
	Equal variances not assumed			.628	802.971	.530	.20681	.32912	-.43923	.85285
BI	Equal variances	.837	.360	.747	901	.455	.19962	.26722	-.32483	.72407

	assumed									
	Equal variances not assumed			.741	801.496	.459	.19962	.26925	-.32890	.72814
UB	Equal variances assumed	.595	.441	.545	901	.586	.12940	.23764	-.33699	.59578
	Equal variances not assumed			.541	804.917	.589	.12940	.23919	-.34012	.59891

An independent-samples t-test was conducted to compare the performance expectancy, Effort Expectancy, social influence, facilitation condition, behavioural intention & usage behaviour for males and females. first, assumptions of normality and leven's test were checked. Both the assumptions are met. There was no significant difference As p value is greater than 0.05, so the null hypothesis is accepted.

ANOVA- Age wise

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
PE	15-25	277	8.6354	4.64312	.27898	8.0862	9.1846	4.00	20.00
	25-35	276	8.4746	4.67131	.28118	7.9211	9.0282	4.00	20.00
	35-45	191	8.5340	4.66765	.33774	7.8678	9.2002	4.00	20.00
	45 & Above	159	8.7484	4.91055	.38943	7.9793	9.5176	4.00	20.00
	Total	903	8.5847	4.69812	.15634	8.2779	8.8916	4.00	20.00
	15-25	277	8.5271	4.78109	.28727	7.9616	9.0926	4.00	20.00
EE	25-35	276	8.3986	4.89755	.29480	7.8182	8.9789	4.00	20.00
	35-45	191	8.4398	4.78433	.34618	7.7569	9.1226	4.00	20.00
	45 & Above	159	8.7925	5.18893	.41151	7.9797	9.6052	4.00	20.00
	Total	903	8.5161	4.88510	.16257	8.1970	8.8351	4.00	20.00
	15-25	277	5.6137	2.79471	.16792	5.2832	5.9443	3.00	15.00
SI	25-35	276	5.6159	2.77868	.16726	5.2867	5.9452	3.00	15.00
	35-45	191	5.6283	2.82341	.20429	5.2253	6.0312	3.00	15.00
	45 & Above	159	5.8113	3.02766	.24011	5.3371	6.2856	3.00	15.00
	Total	903	5.6523	2.83446	.09432	5.4671	5.8374	3.00	15.00
	15-25	277	9.3466	4.80290	.28858	8.7785	9.9147	5.00	25.00
FC	25-35	276	9.2681	4.79551	.28866	8.6999	9.8364	5.00	25.00
	35-45	191	9.2461	4.79223	.34675	8.5621	9.9301	5.00	25.00
	45 & Above	159	9.6667	5.13818	.40748	8.8618	10.4715	5.00	24.00
	Total	903	9.3577	4.85322	.16150	9.0407	9.6747	5.00	25.00
	15-25	277	7.5740	3.84280	.23089	7.1195	8.0285	4.00	20.00

	25-35	276	7.6051	4.00180	.24088	7.1309	8.0793	4.00	20.00
BI	35-45	191	7.5340	3.86178	.27943	6.9829	8.0852	4.00	20.00
	45 & Above	159	7.9308	4.26810	.33848	7.2623	8.5994	4.00	20.00
	Total	903	7.6379	3.96892	.13208	7.3787	7.8971	4.00	20.00
	15-25	277	6.8231	3.46741	.20834	6.4130	7.2332	4.00	20.00
	25-35	276	6.8261	3.55612	.21405	6.4047	7.2475	4.00	20.00
UB	35-45	191	6.7801	3.48437	.25212	6.2828	7.2774	4.00	20.00
	45 & Above	159	7.0377	3.66628	.29075	6.4635	7.6120	4.00	19.00
	Total	903	6.8527	3.52901	.11744	6.6222	7.0832	4.00	20.00

As the P value of F test are more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of age with respect to PERFORMANCE EXPECTANCY, EFFORT EXPECTANCY, SOCIAL INFLUENCE, FACILITATING CONDITIONS, BEHAVIOURAL INTENTION AND USAGE BEHAVIOUR.

ANOVA- Occupation wise

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
	Business	145	8.4897	4.57517	.37995	7.7387	9.2406	4.00	20.00
	Private Employee	329	8.5319	4.72213	.26034	8.0198	9.0441	4.00	20.00
	Government Employee	116	8.6983	4.75343	.44135	7.8241	9.5725	4.00	20.00
PE	Retired	17	8.7059	5.04684	1.22404	6.1110	11.3007	4.00	19.00

	Student	170	8.7941	4.85883	.37266	8.0585	9.5298	4.00	20.00
	Homemaker	81	8.5309	4.81427	.53492	7.4663	9.5954	4.00	20.00
	Not doing Anything	45	8.2444	4.02919	.60064	7.0339	9.4549	4.00	19.00
	Total	903	8.5847	4.69812	.15634	8.2779	8.8916	4.00	20.00
	Business	145	8.3931	4.73506	.39323	7.6159	9.1703	4.00	20.00
	Private Employee	329	8.4559	4.93111	.27186	7.9211	8.9907	4.00	20.00
EE	Government Employee	116	8.6293	4.96340	.46084	7.7165	9.5421	4.00	20.00
	Retired	17	8.6471	5.13494	1.24541	6.0069	11.2872	4.00	20.00
	Student	170	8.7353	5.01659	.38476	7.9757	9.4948	4.00	20.00
	Homemaker	81	8.5679	5.05455	.56162	7.4502	9.6856	4.00	20.00
	Not doing Anything	45	8.0889	4.12213	.61449	6.8505	9.3273	4.00	20.00
	Total	903	8.5161	4.88510	.16257	8.1970	8.8351	4.00	20.00
	Business	145	5.5310	2.72095	.22596	5.0844	5.9777	3.00	15.00
	Private Employee	329	5.6748	2.86069	.15771	5.3645	5.9850	3.00	15.00
SI	Government Employee	116	5.7241	2.90602	.26982	5.1897	6.2586	3.00	15.00
	Retired	17	5.8235	3.16692	.76809	4.1952	7.4518	3.00	14.00

	Student	170	5.7706	3.00891	.23077	5.3150	6.2262	3.00	15.00
	Homemaker	81	5.6420	2.80316	.31146	5.0221	6.2618	3.00	15.00
	Not doing Anything	45	5.2000	2.08458	.31075	4.5737	5.8263	3.00	14.00
	Total	903	5.6523	2.83446	.09432	5.4671	5.8374	3.00	15.00
	Business	145	9.1448	4.61426	.38319	8.3874	9.9022	5.00	24.00
	Private Employee	329	9.3495	4.88989	.26959	8.8192	9.8799	5.00	25.00
	Government Employee	116	9.4397	4.94894	.45950	8.5295	10.3498	5.00	25.00
FC	Retired	17	9.5882	5.53465	1.34235	6.7426	12.4339	5.00	23.00
	Student	170	9.6118	5.16152	.39587	8.8303	10.3933	5.00	25.00
	Homemaker	81	9.3951	4.80801	.53422	8.3319	10.4582	5.00	25.00
	Not doing Anything	45	8.7778	3.82509	.57021	7.6286	9.9270	5.00	23.00
	Total	903	9.3577	4.85322	.16150	9.0407	9.6747	5.00	25.00
	Business	145	7.4966	3.79716	.31534	6.8733	8.1198	4.00	20.00
	Private Employee	329	7.6626	4.03549	.22248	7.2249	8.1003	4.00	20.00
BI	Government Employee	116	7.6983	4.09925	.38061	6.9444	8.4522	4.00	20.00
	Retired	17	7.7647	4.08548	.99088	5.6641	9.8653	4.00	18.00

	Student	170	7.7706	4.11668	.31573	7.1473	8.3939	4.00	20.00
	Homemaker	81	7.7407	4.08894	.45433	6.8366	8.6449	4.00	20.00
	Not doing Anything	45	7.0222	2.88010	.42934	6.1569	7.8875	4.00	17.00
	Total	903	7.6379	3.96892	.13208	7.3787	7.8971	4.00	20.00
	Business	145	6.7103	3.39509	.28195	6.1531	7.2676	4.00	19.00
	Private Employee	329	6.8571	3.54857	.19564	6.4723	7.2420	4.00	20.00
UB	Government Employee	116	7.0000	3.74862	.34805	6.3106	7.6894	4.00	20.00
	Retired	17	6.9412	3.64813	.88480	5.0655	8.8169	4.00	16.00
	Student	170	7.0059	3.71865	.28521	6.4429	7.5689	4.00	20.00
	Homemaker	81	6.8395	3.53007	.39223	6.0589	7.6201	4.00	20.00
	Not doing Anything	45	6.3111	2.41983	.36073	5.5841	7.0381	4.00	16.00
	Total	903	6.8527	3.52901	.11744	6.6222	7.0832	4.00	20.00

As the P value of F test are more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of age with respect to PERFORMANCE EXPECTANCY, EFFORT EXPECTANCY, SOCIAL INFLUENCE, FACILITATING CONDITIONS, BEHAVIOURAL INTENTION AND USAGE BEHAVIOUR.

ANOVA- Education wise

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
	Graduate	121	8.6694	4.74761	.43160	7.8149	9.5240	4.00	20.00
PE	Post Graduate	109	8.6422	4.84677	.46424	7.7220	9.5624	4.00	20.00
	Doctorate	522	8.5441	4.62105	.20226	8.1467	8.9414	4.00	20.00
	Other	151	8.6159	4.85779	.39532	7.8348	9.3970	4.00	20.00
	Total	903	8.5847	4.69812	.15634	8.2779	8.8916	4.00	20.00
	Graduate	121	8.5455	4.92950	.44814	7.6582	9.4327	4.00	20.00
	Post Graduate	109	8.6972	5.16309	.49453	7.7170	9.6775	4.00	20.00
EE	Doctorate	522	8.4464	4.78100	.20926	8.0353	8.8575	4.00	20.00
	Other	151	8.6026	5.04259	.41036	7.7918	9.4135	4.00	20.00
	Total	903	8.5161	4.88510	.16257	8.1970	8.8351	4.00	20.00
	Graduate	121	5.6860	2.95813	.26892	5.1535	6.2184	3.00	15.00
	Post Graduate	109	5.7248	2.81488	.26962	5.1903	6.2592	3.00	15.00
SI	Doctorate	522	5.5900	2.75147	.12043	5.3535	5.8266	3.00	15.00
	Other	151	5.7881	3.04545	.24784	5.2984	6.2778	3.00	15.00

	Total	903	5.6523	2.83446	.09432	5.4671	5.8374	3.00	15.00
	Graduate	121	9.4215	5.00791	.45526	8.5201	10.3229	5.00	25.00
	Post Graduate	109	9.5413	4.89620	.46897	8.6117	10.4709	5.00	25.00
FC	Doctorate	522	9.2701	4.73743	.20735	8.8628	9.6775	5.00	25.00
	Other	151	9.4768	5.12749	.41727	8.6523	10.3013	5.00	25.00
	Total	903	9.3577	4.85322	.16150	9.0407	9.6747	5.00	25.00
	Graduate	121	7.7273	4.16333	.37848	6.9779	8.4766	4.00	20.00
	Post Graduate	109	7.8807	4.13146	.39572	7.0963	8.6651	4.00	20.00
BI	Doctorate	522	7.5460	3.86763	.16928	7.2134	7.8785	4.00	20.00
	Other	151	7.7086	4.06545	.33084	7.0549	8.3623	4.00	20.00
	Total	903	7.6379	3.96892	.13208	7.3787	7.8971	4.00	20.00
	Graduate	121	6.9091	3.59629	.32694	6.2618	7.5564	4.00	20.00
UB	Post Graduate	109	6.9358	3.57272	.34220	6.2575	7.6141	4.00	20.00
	Doctorate	522	6.7893	3.46544	.15168	6.4913	7.0872	4.00	20.00
	Other	151	6.9669	3.68857	.30017	6.3738	7.5600	4.00	20.00
	Total	903	6.8527	3.52901	.11744	6.6222	7.0832	4.00	20.00

As the P value of F test are more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of age with respect to Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Behavioural Intention And Usage Behaviour.

Monthly Income wise ANOVA

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
	Less than 25,000	344	8.6599	4.73779	.25544	8.1574	9.1623	4.00	20.00
	25,001-50,000	131	8.4198	4.59591	.40155	7.6254	9.2143	4.00	20.00
PE	50,001-75,000	193	8.5026	4.69832	.33819	7.8355	9.1696	4.00	20.00
	More than 75,001	235	8.6340	4.72244	.30806	8.0271	9.2410	4.00	20.00
	Total	903	8.5847	4.69812	.15634	8.2779	8.8916	4.00	20.00
	Less than 25,000	344	8.6134	4.91371	.26493	8.0923	9.1345	4.00	20.00
	25,001-50,000	131	8.3435	4.84494	.42330	7.5061	9.1810	4.00	20.00
EE	50,001-75,000	193	8.4301	4.91453	.35376	7.7323	9.1278	4.00	20.00
	More than 75,001	235	8.5404	4.86851	.31759	7.9147	9.1661	4.00	20.00
	Total	903	8.5161	4.88510	.16257	8.1970	8.8351	4.00	20.00
	Less than 25,000	344	5.6715	2.84788	.15355	5.3695	5.9735	3.00	15.00
	25,001-50,000	131	5.5802	2.77337	.24231	5.1008	6.0595	3.00	15.00
SI	50,001-75,000	193	5.6166	2.79846	.20144	5.2193	6.0139	3.00	15.00
	More than 75,001	235	5.6936	2.89410	.18879	5.3217	6.0656	3.00	15.00
	Total	903	5.6523	2.83446	.09432	5.4671	5.8374	3.00	15.00
	Less than 25,000	344	9.4593	4.92493	.26553	8.9370	9.9816	5.00	25.00
	25,001-50,000	131	9.1298	4.70253	.41086	8.3169	9.9426	5.00	24.00
FC	50,001-75,000	193	9.2694	4.76313	.34286	8.5932	9.9457	5.00	25.00
	More than 75,001	235	9.4085	4.92802	.32147	8.7752	10.0419	5.00	25.00
	Total	903	9.3577	4.85322	.16150	9.0407	9.6747	5.00	25.00

	Less than 25,000	344	7.6773	3.96162	.21360	7.2572	8.0974	4.00	20.00
	25,001-50,000	131	7.5267	3.91904	.34241	6.8493	8.2041	4.00	20.00
BI	50,001-75,000	193	7.6062	3.96474	.28539	7.0433	8.1691	4.00	20.00
	More than 75,001	235	7.6681	4.03410	.26316	7.1496	8.1865	4.00	20.00
	Total	903	7.6379	3.96892	.13208	7.3787	7.8971	4.00	20.00
	Less than 25,000	344	6.8750	3.52071	.18982	6.5016	7.2484	4.00	20.00
	25,001-50,000	131	6.8168	3.55355	.31048	6.2026	7.4310	4.00	20.00
UB	50,001-75,000	193	6.7824	3.43607	.24733	6.2945	7.2702	4.00	20.00
	More than 75,001	235	6.8979	3.62302	.23634	6.4322	7.3635	4.00	20.00
	Total	903	6.8527	3.52901	.11744	6.6222	7.0832	4.00	20.00

As the P value of F test are more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of age with respect to Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Behavioural Intention And Usage Behaviour.

Path analysis diagram

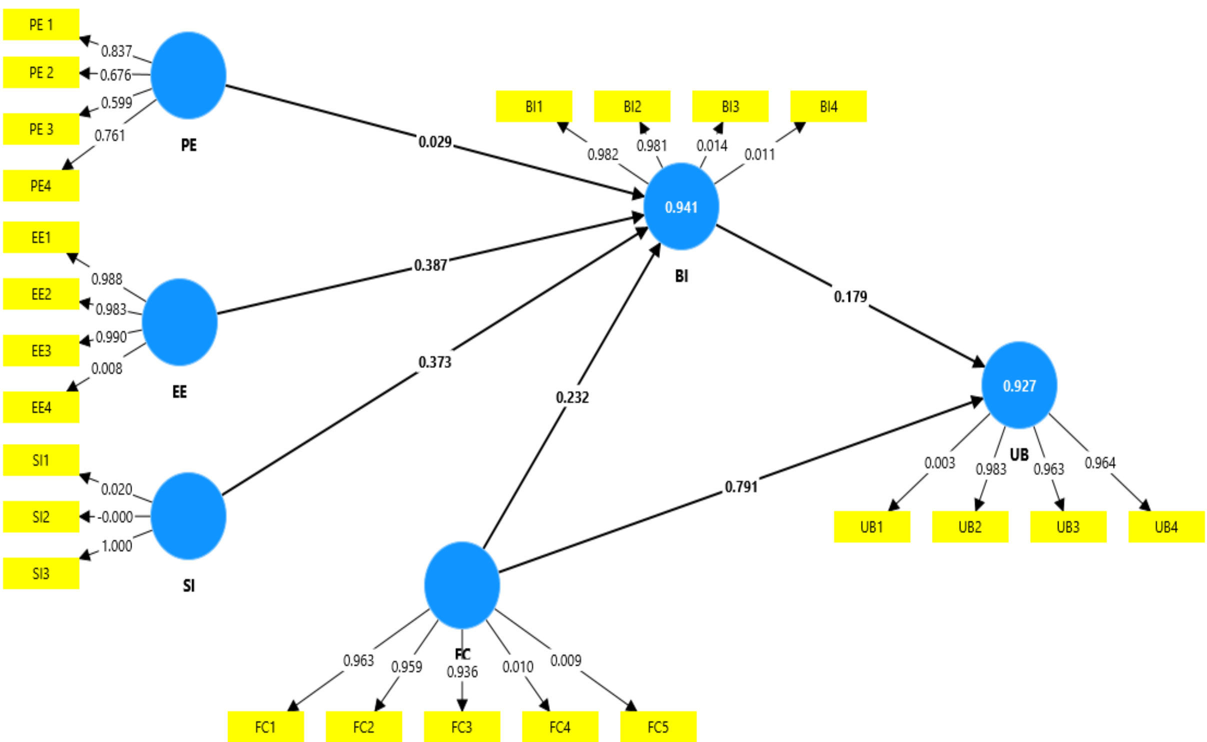


Figure: PLS SEM Measurement Model

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.794	0.795	0.866	0.618
EE	0.734	0.754	0.831	0.553
FC	0.782	0.794	0.851	0.533
PE	0.716	0.718	0.824	0.54
SI	0.732	0.783	0.822	0.606
UB	0.85	0.863	0.898	0.688

Table : PLS-SEM assessment results of reflective measurement models

Discriminant Validity (Using HTMT Values)

The Discriminant Validity was assessed with the use of Fornell-Larcker criterion & HTMT Criteria as shown below.

Table: Discriminant Validity as per Fornell-Larcker criterion

	BI	EE	FC	PE	SI	UB
BI	0.786					
EE	0.515	0.744				
FC	-0.541	-0.616	0.730			
PE	0.494	0.485	-0.558	0.735		
SI	0.537	0.639	-0.536	0.491	0.779	
UB	-0.167	-0.151	0.178	-0.115	-0.141	0.829

As seen in the table it is clearly visible that all the values are below the conservative threshold value of 0.85.

	BI	EE	FC	PE	SI	UB
BI						
EE	0.656					
FC	0.674	0.792				
PE	0.652	0.648	0.737			
SI	0.734	0.895	0.729	0.707		

UB	0.198	0.182	0.211	0.150	0.185	

Table: Hetero Trait-Mono trait Ratio (HTMT)

The bootstrapping procedure confirmed that there were no changes and indicated that the HTMT values are significantly different from 1, at a 95% confidence interval and 0.05 significance level. This demonstrates that discriminant validity has been established.

Multicollinearity

The presence of Multicollinearity among the independent variables in a regression model was assessed using variance inflation factors (VIF) as suggested by Belsely et at. (1980) and Greene (1993).

	VIF
BI1	1.484
BI2	1.603
BI3	1.610
BI4	1.626
EE1	1.425
EE2	1.496
EE3	1.338
EE4	1.374
FC1	1.518
FC2	1.404
FC3	1.437
FC4	1.479
FC5	1.463
PE1	1.314
PE2	1.359
PE3	1.287
PE4	1.447
SI1	1.250
SI2	1.439
SI3	1.322

UB1	1.948
UB2	1.817
UB3	2.023
UB4	1.882

Table: variance inflation factors (VIF)

VIF, or "Variance Inflation Factor," is a statistical measure used to assess multicollinearity in regression analysis. Multicollinearity occurs when two or more independent variables are highly correlated, which can destabilize regression coefficient estimates and weaken model predictions. VIF quantifies the degree of multicollinearity among these independent variables. The Variance Inflation Factor (VIF) for an independent variable is determined by comparing the variance of its coefficient estimate in a model with all variables to that in a model with only itself. A VIF of 1 signifies no correlation with other variables, while a VIF above 1 indicates high correlation with one or more other variables, with higher values reflecting more severe multicollinearity.

To Measure Direct effect, following hypotheses have been developed

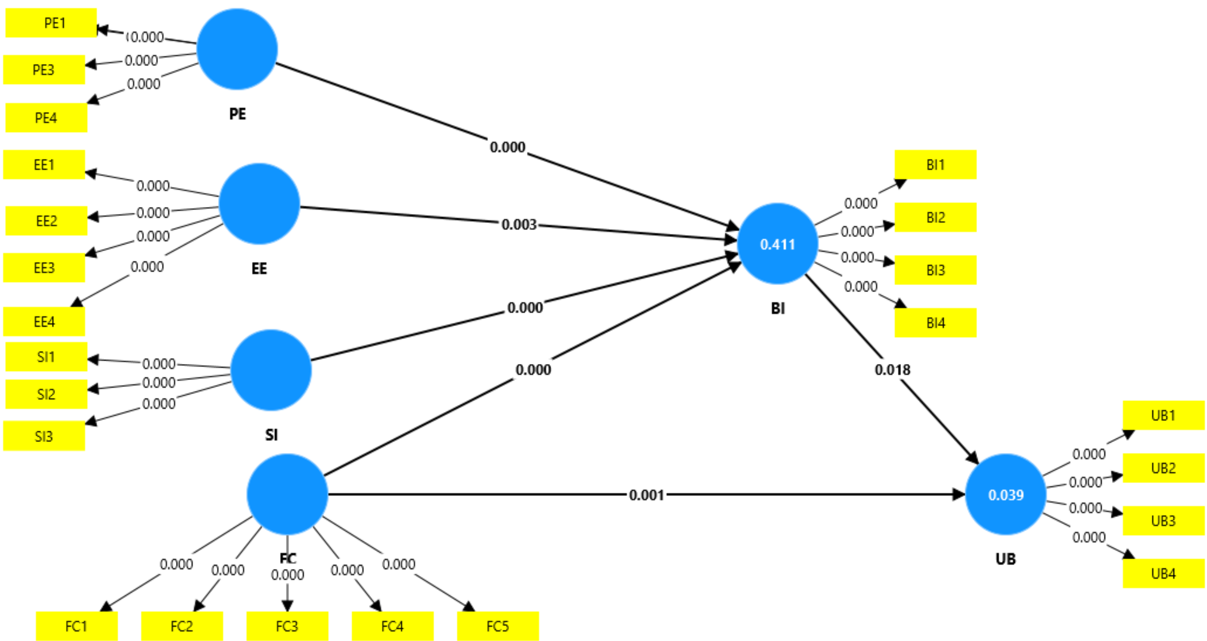


Figure: PLS SEM Structural Model

Path	P values	Result
BI -> UB	0.018	Significant
EE -> BI	0.003	Significant
FC -> BI	0.000	Significant
FC -> UB	0.001	Significant
PE -> BI	0.000	Significant
SI -> BI	0.000	Significant

Table: Summary of Path Analysis of main variables

The text discusses the analysis of a measurement model and the testing of causal relationships among latent constructs using a path model in structural equation modelling (SEM). The results from the PLS SEM 4.0 software indicate that all proposed hypotheses are supported. Bootstrap samples were generated at the 95% confidence level to assess the mediating effect, with findings presented in accompanying figures and tables. from the table it is clear that Performance Expectancy has significant impact on Behavioural Intention. Effort Expectancy has significant impact on Behavioural Intention, Social Influence has significant impact on Behavioural Intention, Facilitating Conditions has significant impact on Behavioural Intention. Facilitating Conditions has significant impact on Usage Behaviour and Behavioural Intention has significance impact on Usage Behavior.

Bootstrapping

Bootstrapping is a nonparametric method used to test the statistical significance of PLS-SEM results, including path coefficients, Cronbach's alpha, HTMT, and R^2 values. Path coefficients are considered significant if the two-tailed T-test statistic exceeds 1.96 at a 5% significance level.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BI -> UB	0.100	0.100	0.042	2.360	0.018
EE -> BI	0.131	0.133	0.044	3.007	0.003

FC -> BI	0.227	0.227	0.036	6.247	0.000
FC -> UB	0.124	0.126	0.039	3.183	0.001
PE -> BI	0.185	0.186	0.034	5.437	0.000
SI -> BI	0.240	0.239	0.036	6.584	0.000

As seen in the table all the t statastics value are above 1.96 and significant at significance level of 0.05. this also confirms our findings when looking at the Path analysis result.

To measure mediating/indirect effect following hypothesis have been developed.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Result
EE -> BI -> UB	-0.013	-0.013	0.007	1.800	0.072	Insignificance
FC -> BI -> UB	0.023	0.023	0.011	2.149	0.032	Significance
PE -> BI -> UB	-0.019	-0.019	0.009	2.075	0.038	Significance
SI -> BI -> UB	-0.024	-0.024	0.011	2.220	0.026	Significance

The findings are consistent with previous finding (Li Kim & Park, 2007; Chen & Barnes, 2007) compare to that all the mediating effects plays significance role exempt effort expectancy.

9. Key findings

Key findings of one-way ANOVA

Age-wise one-way ANOVA results show that we accept the alternate hypothesis, which means there is no significant difference between various categories of age with respect to performance expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Usage Behaviour and Behavioural Intention.

Occupation wise one-way ANOVA results show that we accept the alternate hypothesis, which means there is no significant difference between various categories of age with respect to performance expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Usage Behaviour and Behavioural Intention.

The outcome of **income-wise Anova** suggests that there is a statistically significant variation in the Monthly income of respondents and individuals across different income categories. which means there is no significant difference between various categories of age with respect to performance expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Usage Behaviour and Behavioural Intention.

Education wise one-way ANOVA results show that we accept the alternate hypothesis, which means there is no significant difference between various categories of age with respect to performance expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Usage Behaviour and Behavioural Intention.

key findings of PLS-SEM Path analysis

The text discusses the analysis of a measurement model and the testing of causal relationships among latent constructs using a path model in structural equation modelling (SEM). The results from the PLS SEM 4.0 software indicate that all proposed hypotheses are supported. Bootstrap samples were generated at the 95% confidence level to assess the mediating effect, with findings presented in accompanying figures. Performance Expectancy has significant impact on Behavioural Intention. Effort Expectancy has significant impact on Behavioural Intention, Social Influence has significant impact on Behavioural Intention, Facilitating Conditions has significant impact on Behavioural Intention. Facilitating Conditions has significant impact on Usage Behaviour and Behavioural Intention has significance impact on Usage Behavior.

10.Conclusion

Augmented Reality (AR) has emerged as a transformative technology in the retail sector, reshaping how consumers interact with products and make purchasing decisions. By enabling virtual try-ons, 3D product visualization, and immersive in-store experiences, AR bridges the gap between online and offline shopping, reducing uncertainty and enhancing consumer confidence. Research indicates that AR-driven experiences significantly influence purchase intentions by providing a more engaging and interactive shopping journey, ultimately leading to higher conversion rates and customer satisfaction (Javornik, 2016). As retailers increasingly adopt AR, its role in driving sales and fostering brand loyalty continues to grow.

One of the key advantages of AR in retail is its ability to minimize product return rates by allowing consumers to preview items in real-world settings before purchasing. For instance, furniture retailers like IKEA use AR to let customers visualize how products would fit in their homes, leading to more informed decisions (Yim et al., 2017). Similarly, beauty brands leverage AR-powered virtual makeup trials, which enhance user engagement and reduce hesitation in buying cosmetics. These applications demonstrate how AR enhances the decision-making process, making it a valuable tool for modern retailers seeking to improve customer experience and operational efficiency.

Despite its benefits, the widespread adoption of AR in retail faces several challenges, including high implementation costs, technological limitations, and varying consumer readiness. Some shoppers may find AR interfaces complex or may be hesitant to adopt new digital shopping methods (Pantano et al., 2017). Additionally, retailers must ensure seamless integration across multiple platforms, including mobile apps and in-store kiosks, to provide a cohesive experience. Addressing these barriers will be crucial for maximizing AR's potential and ensuring long-term consumer acceptance.

Looking ahead, the future of AR in retail appears promising, with advancements in AI, machine learning, and wearable AR devices expected to further enhance personalization and interactivity. Retailers that invest in AR technology and tailor experiences to consumer preferences will likely gain a competitive edge. Future research should explore the long-term behavioral impacts of AR, including its role in customer retention and omnichannel retail strategies. As consumer expectations evolve, AR will remain a key driver of innovation in the retail industry.

In conclusion, Augmented Reality has a profound impact on consumer purchase intentions and adoption in retail by offering immersive, interactive, and personalized shopping experiences. While challenges remain, the benefits of AR—such as increased engagement, reduced returns, and higher conversion rates—make it a vital tool for modern retailers. By addressing adoption barriers and continuously improving AR applications, businesses can unlock new opportunities for growth and customer satisfaction in an increasingly digital marketplace.

11. Theoretical Implication

The integration of Augmented Reality (AR) in the retail sector aligns closely with the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants of technology adoption. AR enhances performance expectancy by allowing consumers to visualize products in real-time, reducing uncertainty and increasing confidence in purchase decisions. Studies show that AR-driven virtual try-ons and 3D product previews significantly improve perceived usefulness, a core UTAUT construct, leading to higher purchase intentions. This suggests that retailers investing in AR should emphasize its ability to deliver tangible benefits, such as reducing product returns and enhancing customer satisfaction.

Effort expectancy plays a critical role in AR adoption, as consumers are more likely to embrace the technology if it is intuitive and easy to use. The UTAUT model posits that technologies requiring minimal learning curves see faster adoption—a principle that applies directly to AR retail applications. For instance, mobile AR apps with simple interfaces and seamless integration (e.g., QR code scanning or camera-based overlays) reduce friction, making the shopping experience more engaging. Retailers must ensure that AR tools are user-friendly, as complexity could deter less tech-savvy consumers, negatively impacting adoption rates.

Finally, social influence and facilitating conditions further shape AR's impact on consumer behavior. Social proof, such as influencer endorsements or peer recommendations, can accelerate AR adoption by reinforcing its credibility (social influence). Meanwhile, facilitating conditions—such as retailer support, device compatibility, and high-speed internet—determine whether consumers can access AR features effortlessly. The UTAUT model suggests that even if consumers perceive AR as beneficial, poor infrastructure or lack of retailer promotion can hinder adoption. Thus, businesses must not only develop AR solutions but also create an ecosystem that supports seamless usage, including customer education and technical assistance, to maximize its impact on purchase intentions.

12.Managerial implications

First, retailers should prioritize seamless AR integration across both digital and physical channels to enhance customer experience. Investing in user-friendly AR applications—such as virtual try-ons for apparel or 3D product previews for furniture—can significantly reduce purchase hesitation and product returns (Yim et al., 2017). Managers must ensure these tools are easily accessible via mobile apps or in-store kiosks, with intuitive interfaces to encourage adoption. Additionally, gathering consumer feedback on AR features will help refine functionality and improve engagement, ultimately driving higher conversion rates.

Second, marketing strategies should leverage AR's interactive capabilities to create immersive brand experiences. For instance, AR-powered advertisements or gamified shopping experiences can increase consumer interaction and emotional connection with products (Javornik, 2016). Retailers can also use AR data analytics to track user behavior, such as time spent on virtual try-ons or click-through rates, to personalize recommendations and promotions. By aligning AR campaigns with consumer preferences, businesses can boost brand loyalty and differentiate themselves in a competitive market.

Finally, while AR adoption requires significant investment, managers should weigh long-term benefits against costs. Training staff to assist customers with AR tools and ensuring backend infrastructure supports smooth functionality are crucial steps (Pantano et al., 2017). Retailers may also consider phased implementation—starting with high-impact categories like fashion or home decor—before expanding AR features across all product lines. By strategically adopting AR, businesses can enhance customer satisfaction, reduce operational inefficiencies, and secure a sustainable competitive advantage in the evolving retail landscape.

13.Scope for further Research

Based on the study, the following scope of research is available, considering the present study. Prior studies have primarily focused on Western markets, leaving a gap in understanding how cultural differences affect AR adoption. Future research could compare AR acceptance in individualistic vs. collectivistic cultures (Hofstede, 2011). Additionally, demographic factors such as age, gender, and digital literacy may influence AR engagement (Pantano et al., 2017).The convergence of AR with AI-driven personalization (Grewal et al., 2020) and Metaverse retail environments (Dwivedi et al., 2022) presents new research avenues. How do AI-powered AR recommendations influence purchase decisions? With AR collecting biometric and behavioral data, future studies should examine consumer privacy concerns (Rese et al., 2020). What regulatory frameworks are needed to ensure ethical AR usage? Does AR reduce product returns by improving decision accuracy (Beck & Crié, 2018)? How does post-purchase AR engagement (e.g., interactive manuals) affect customer satisfaction? With WebAR eliminating app dependency (Flavián et al., 2021), how does accessibility impact adoption? Similarly, how does voice-assisted AR (e.g., Alexa-guided shopping) influence user experience? As AR adoption grows, research should explore the need for standardization (e.g., AR quality benchmarks) and consumer protection policies (Bonetti et al., 2019).

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15.Annexure 1: Copy of Published Papers

1. UGC paper

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"A STUDY ON FACTORS AFFECTING AUGMENTED REALITY ADOPTION IN THE RETAIL SECTOR WITH SPECIAL REFERENCE TO FOUR MAJOR CITIES OF GUJARAT"

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Abstract
Augmented Reality is a technology that creates a layer in digital transformation. Augmented Reality (AR) is creating a different eye on image, sound and other data into real world with the help of the devices like tablet, mobile phone, laptops, AR glasses etc. AR creates a real world by adding the elements on it.in retail, AR can provide immersive shopping environment, Virtual try-ons, virtual displays that can completely change the way customers interact with brands. Present study investigates the factors investigated the adoption of AR in the retail sector focusing on four major cities of Gujarat: Ahmedabad, Vadodara, Surat, Rajkot. The paper presents the theoretical conceptualisation of various factors of adoption like Self efficacy, personal innovativeness, Perceived ease of use, attitude, perceived usefulness, technological knowledge, competitive pressure, customer pressure, external support, trading partner pressure, perceived cost, intention to use AR. The cross-sectional survey method was used from 233 retail businesses in Gujarat state (Ahmedabad, Vadodara, Surat, Rajkot). the data was analysed using Smart-PLS-3 Software Analysis.

Keywords: Adoption in retail, Augmented Reality, Gujarat, Retail Industry, Technology acceptance

Introduction

The retail sector is rapidly growing online with the help of technological advancements particularly with the help of Augmented Reality (AR). AR improves the shopping experience by creating a digital content into the physical world. AR offers customers an interactive way to engage with products/services. AR not only improves customer engagement but also provides retailers with new avenues for brand differentiation (Pantano and Naccarato,2016)

The potential of AR to transform retail experiences has been widely recognized. According to Yim et al. (2017), AR can facilitate personalized shopping experiences, thereby increasing customer satisfaction and loyalty. However, despite its promising advantages, the adoption of AR technology remains inconsistent across different markets. Factors such as technological readiness, perceived usefulness, and user experience play critical roles in determining how retailers integrate AR into their operations (Scholz & Steinmetz, 2019). In Gujarat, a region characterized by a rapidly evolving retail landscape and diverse consumer demographics, understanding these factors is essential. Previous studies have highlighted regional variations in technology adoption, emphasizing the need for localized research to tailor strategies effectively (Rao et al., 2020). By focusing on the unique characteristics of Ahmedabad, Surat, Vadodara, and Rajkot, this study aims to provide insights into the barriers and facilitators of AR adoption in the retail sector.

Augmented Reality in India

Advanced technologies have rapidly gained traction post-pandemic, with Indian companies adopting tools like Mixed Reality, AI, AR, VR, and Big Data to boost productivity. AR technology requires smart devices or cameras for use. In 2021, the global AR market was valued at $28 billion, projected to reach $250 billion by 2028. In India, AR adoption increased significantly, rising from $0.34 billion in 2017 to $1.83 billion in 2020, reflecting a compounded annual growth rate (CAGR) of 75%.

2. Peer-reviewed journal

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A study on adoption of mobile augmented reality in tourism sector

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Abstract: *The COVID-19 pandemic significantly impacted the tourism industry worldwide, a major tourist destination that had experienced a tourism boom before the crisis. Augmented Reality (AR) presents opportunities for tourist operators to innovate and recover. This study tests an extended version of the Unified Theory of Acceptance and Use of Technology (UTAUT) model to identify factors influencing the adoption of Augmented Reality in Tourism in India. By analysing data from 201 respondents through structural equation modelling, the study finds that habit, hedonic motivations, and facilitating conditions are key determinants for AR use.*

Key Words: *Augmented Reality, UTAUT, Adoption, SEM-PLS, Tourism.*

1. INTRODUCTION:
The pandemic has significantly disrupted the tourism industry, which had become a prominent destination by 2019. It features sAugmented Reality destination elements such as free Wi-Fi, interactive tourist stands, and robust online support services. Despite these advantages, the introduction of travel restrictions and social distancing has severely affected tourism, with forecasts indicating a full recovery may not occur until 2026.the factors influencing the adoption of Augmented Reality Tourism apps, focusing on age and gender's moderating roles in adoption intentions and usage. It highlights significant disruptions in the tourism industry due to the pandemic, which has severely impacted destinations where tourism comprised 16.2% of india's GDP in 2019. it is characterized by its sAugmented Reality destination features, such as widespread Wi-Fi and QR codes. The rise of sAugmented Realityphones has facilitated the integration of augmented reality in tourism, which may aid recovery post-pandemic. The paper aims to test the UTAUT-3 model to analyze AR adoption in India and respond to specific research questions regarding these dynamics.

Researchers have examined the adoption of Augmented Reality (AR) through various models, notably the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT), particularly in tourism contexts. A study by Paulo et al. integrated UTAUT-2 with Technology-Task Fit (TTF) to analyze AR adoption finding that future use is influenced by Performance Expectancy (PE), Facilitating Conditions (FC), Hedonic Motivations (HM), Habit (HB), and TTF, with no significant effects from age or gender. Similarly, Gharaibeh et al. explored Augmented Reality adoption in Jordan using UTAUT-2, highlighting performance expectancy and aesthetics as key factors. However, notable gaps exist as none of these studies were conducted post-pandemic.

2. Conceptual Framework :
The UTAUT framework, developed by Venkatesh to explain information systems adoption, initially included four key constructs: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). In 2012, the model was expanded to include three additional constructs—hedonic motivation (HM), price value (PV), and habit (HB)—to address its limitations. Moderators such as age, gender, experience, and voluntariness also influence the relationship between these constructs and user behavior. UTAUT-3 was later introduced, incorporating personal innovativeness in IT, enhancing its predictive power compared to previous versions.