Proceedings of the International Conference on Contemporary Marketing Issues

Vol 1, No 1 (2024)

Proceedings of the International Conference on Contemporary Marketing Issues (2024)

Innovative Roadways: An Exploration of Technological Neophilia, Technophobia, and Media Richness in the Shaping of AI-VR Adoption

Das Sougato, Datta Biplab

doi: [10.12681/iccmi.7606](https://doi.org/10.12681/iccmi.7606)

Innovative Roadways: An Exploration of Technological Neophilia, Technophobia, and Media Richness in the Shaping of AI-VR Adoption

Sougato Das, Biplab Datta
Vinod Gupta School of Management, Indian Institute of Technology, Kharagpur, India

Abstract
This study explores the adoption of AI-VR systems in car sales by extending the UTAUT framework by incorporating technophobia, technological neophilia, perceived benefits, and media richness. Conducted with 401 passenger car sales executives in Kolkata, West Bengal, the analysis employs partial least squares structural equation modeling (PLS-SEM) to elucidate complex relationships among variables and their impact on adoption. The results indicate that performance expectancy positively correlates with behavioral intention, whereas effort expectancy lacks significant influence. Social influence minimally affects behavioral intention, contrasting with a positive relationship with perceived benefits. Technological neophilia positively influences behavioral intention, whereas technophobia has a negative impact. Technological neophilia correlates positively with performance expectancy, effort expectancy, media richness, and technophobia. Social influence is positively related to technological neophilia. These findings contribute valuable insights for targeted interventions and significantly enhance our understanding of AI-VR
Keywords: AI-Virtual Reality; Media Richness; PLS-SEM; Technological Neophilia; Technophobia; UTAUT

1 Introduction

The Indian passenger car industry is experiencing rapid growth, driven by a burgeoning middle class, increased disposable income, and a growing demand for technology (Chaudhuri et al., 2022). Despite the evolving automotive sales infrastructure, the traditional car sales process often fails to meet consumer expectations for personalized experiences and convenience (Mukherjee et al., 2013). The integration of Artificial Intelligence (AI) and Virtual Reality (VR) in the industry can optimize vehicle performance, enable predictive maintenance, and enhance safety through advanced driver-aid systems (Theissler et al., 2021).

The combination of AI and VR has transformed various industries globally by creating realistic environments and intelligent VR characters, providing personalized and immersive(Kumari et al., 2022; Stanica et al., 2018). AI-powered object recognition and tracking enable seamless interaction within the VR world (Chatterjee, Rana et al., 2021), while AI algorithms analyze user behavior and preferences to generate tailored VR content (Xu et al., 2023).

However, there is a notable gap in understanding the adoption of AI-VR systems in car sales, particularly from the perspective of sales professionals. This research aims to fill this gap by investigating how AI-VR impacts sales executives' roles, customer interactions, sales techniques, and customer relationship management in the context of automobile sales. To address this gap, this study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) framework (Venkatesh et al., 2003a) by adding four variables: Technophobia, Technological Neophilia, Perceived Benefits, and Media Richness. Technophobia accounts for the fear or dislike of technology that could hinder the adoption of AI-VR systems (Khasawneh, 2018b). Technological neophilia reflects curiosity and openness to new technologies, positively influencing acceptance (Feng et al., 2022). Perceived Benefits assess how individuals interpret the value of a technology (Huang, 2023a), while Media Richness evaluates the amount of information provided by the AI-VR system, which is crucial for effective communication in vehicle sales (U. K. Lee & Kim, 2022).

Studying AI-VR systems in passenger car sales is imperative for enhancing consumer experiences, providing personalized recommendations, reducing operational costs through virtual showrooms, and enabling competitive advantages for dealerships(FRICKER, 2019; Meyer-Waarden & Cloarec, 2022). Additionally, AI-powered VR can be employed for salespeople training and market research, gaining insights into consumer behavior and preferences. The study's objectives are twofold: first, to identify and analyze key factors influencing AI-VR system adoption in car sales using the extended UTAUT framework, and second, to explore the interrelationship between technological neophilia, technophobia, media richness, perceived benefits, and other UTAUT variables.

2 Literature Review

2.1 Artificial Intelligence-powered Virtual Reality

AI-VR systems offer immersive experiences and improved interactions (Gandedkar et al., 2021). AI algorithms play a pivotal role in enhancing VR content development, real-time data analysis, adaptive environments, and personalized user experiences. By simulating human behavior, AI creates dynamic settings that respond intelligently to user input, enabling the fusion of VR and the real world (Gong, 2021). Personalization through AI-driven analysis of massive datasets enhances VR engagement and user satisfaction(Mnyakin, 2020). In automotive sales, AI-VR systems revolutionize customer engagement, allowing salespeople to demonstrate car models, customize features, simulate test drives, and provide personalized recommendations (Jain & Kulkarni, 2022). Integrating AI algorithms into VR environments enables real-time customer data analysis, guiding sales executives through the sales process, and enabling natural language processing for realistic conversations (Dwivedi et al., 2022).

2.2 UTAUT

This study is grounded in the UTAUT model, which was chosen for its effectiveness in describing technology adaptation (Venkatesh, 2022). UTAUT surpasses other models in explaining technology acceptance (Dwivedi et al., 2019), emphasizing performance expectancy, effort expectancy, facilitating conditions, and social influence. Experience, voluntariness, gender, and age serve as moderators. To enhance context-specific understanding of AI-VR acceptance among car sales executives, we extend the UTAUT model by incorporating Technophobia, Technological Neophilia, Media Richness, and Perceived Benefits. Facilitating conditions are considered hygiene factors for AI-VR system operation, eliminating the need for a separate construct. “Voluntariness of use” is excluded, given the job-centric adoption. Gender, with only 5% female representation, is disregarded as a moderator due to its limited impact. Statistically significant inferences from a small sample set are acknowledged as challenging (Al-Adwan et al., 2022). **Error! Reference source not found.** summarizes the definitions of the constructs.

Table 1 UTAUT construct definitions (Venkatesh et al., 2003)

Constructs	Definition of the constructs
Performance Expectance	The extent to which adopting technology will help consumers complete particular tasks.
Effort Expectance	Level of effort or simplicity required for consumers to use the technology
Social Influence	The impact of others’ actions, opinions, or presence on an individual’s thoughts, feelings, or behaviors.
Facilitating Conditions	External factors or resources that ease the adoption or use of a particular technology or innovation.
Behavioral Intention	Motivational elements that influence behavior. The stronger the intention to execute, the more likely the behavior will be carried out.

2.3 Technophobia

Technophobia, the fear of technology, poses a significant obstacle in the era of rapid technological advancement (Khasawneh 2020). It encompasses anxieties about learning new technology, automation-related job displacement, privacy invasion, and the loss of human connection (Osiceanu 2015). Overwhelmed or insecure individuals may resist adopting technologies such as AI-VR systems because of technophobia, often stemming from technical ignorance or concerns about rapid technological change (McClure 2018; Khasawneh 2022). Factors such as uncertainty, employment insecurity, and the impact on tradition can intensify technophobia. Privacy breaches and data security issues may further contribute to distrust and resistance to AI-VR systems (Ho et al., 2022). Recognizing and addressing technophobia are crucial for overcoming adoption hurdles, enhancing user experience, addressing ethical concerns, and promoting responsible implementation and broader acceptance of highly technological systems such as AI-VR (Khasawneh 2018).

2.4 Technological Neophilia

Technological neophiles, individuals with a strong attraction to new technologies, play a crucial role in the age of rapid technological progress (Formatje, 2016). This inclination, known as technological neophilia, reflects a keen desire to adopt and experiment with the latest technological innovations (Marius, 2014). Neophiles, driven by curiosity and a penchant for novelty, serve as early adopters who enthusiastically embrace emerging technologies, influencing market trends and customer preferences (S.-M. Lee, 2015a). Their openness to new technology foster innovation, providing valuable feedback and shaping the evolution of systems such as AI-VR (Hungate, 2018a). This study introduces technological neophilia as a crucial factor in understanding the initial adoption of AI-VR systems, emphasizing its role in predicting market trends, enhancing user experience, and ensuring responsible deployment (Giordano et al., 2018; Griffin et al., 2017).

2.5 Media Richness

Media richness refers to a "communication medium's ability to effectively transmit information, considering both breadth and depth of communication" (Liu et al., 2009). It is a critical factor in technology-mediated communication, influencing the quality and effectiveness of interactions (Daft & Lengel, 1986). According to the Media Richness Theory, communication channels differ in their ability to transmit information and aid understanding. (Dennis & Kinney, 1998a). Determined by factors such as immediacy, feedback potential, nonverbal cues, and message personalization, media richness impacts information processing speed and accuracy (Chang et al., 2017). Rich media with nonverbal cues and personalization reduces misinterpretation. In the context of AI-VR systems, media richness is vital for effective communication, influencing user experiences, collaboration, decision-making, and system acceptance (U. K. Lee, 2022a). Developers leverage media richness to design interfaces that align with user expectations, thus fostering AI-VR system adoption. This study investigates the dimensions and significance of media richness in the context of AI-VR systems.

2.6 Perceived Benefits

Artificial intelligence (AI) and virtual reality (VR) systems have brought transformative possibilities to various industries, and understanding the perceived benefits is crucial for driving their adoption. Perceived benefits encompass individuals' subjective evaluations of technology's advantages, including improved efficiency, productivity, cost savings, increased innovation, better decision-making, and enhanced user experiences (Abramova & Böhme, 2016; De Oliveira et al., 2023). These benefits significantly influence individuals' motivation to adopt AI technology, helping them overcome resistance to change (Jarrahi, 2018; Oreg, 2003; Venkatesh, 2022). Perceived benefits serve as decision-making factors for potential adopters, thereby affecting user satisfaction and system retention. When users realize the advantages of AI technology, satisfaction levels increase, leading to higher engagement and continued usage (Vasconcelos et al., 2022). This study investigates perceived benefits and their influence on the deployment of AI-VR systems.

3 Research Model and Hypothesis development

3.1 Direct Impact of Constructs on Behavioral Intention

Performance expectancy and behavioral intention play crucial roles in users' acceptance and usage of AI systems (Fan et al., 2020; Venkatesh et al., 2003b). Performance expectancy refers to users' perceptions of how an AI system will enhance their performance and experience (Venkatesh et al., 2012), while behavioral intention signifies users' willingness to engage in specific actions, such as utilizing an AI-VR system (Chatterjee, Tamilmani, et al., 2020). Users are more likely to accept AI-VR systems if they perceive them as enhancing efficiency, productivity, or enjoyment (Huang, 2023), thereby increasing their intention to adopt such systems.

H1: Performance Expectancy Positively impacts Behavioral intention to adopt an AI-VR system.

Effort expectancy refers to the ease of understanding and using an AI (Venkatesh et al., 2012; Vimalkumar et al., 2021), where simplicity increases adoption likelihood (Venkatesh et al., 2003). A user-friendly interface, clear controls, and instructions enhance ease of use, influencing behavioral intention (Chatterjee et al., 2020). Users' acceptance of AI-VR systems is strongly tied to effort expectancy and behavioral intention (Oncioiu & Priescu, 2022) as perceptions of usability directly impact adoption (Huang, 2023b), showing a positive correlation between effort expectancy and behavioral intention. Hence

H2: Effort Expectancy Positively impacts Behavioral intention to adopt an AI-VR system.

Social influence encompasses social norms and subjective norms affecting decision-making (Meyer-Waarden & Cloarec, 2022; Nordhoff et al., 2021). Perceptions of others' attitudes and expectations towards AI adoption strongly influence individuals' own beliefs and preferences, linking social influence with behavioral intention (Loske & Klumpp, 2021). Individuals are more inclined to adopt AI-VR systems if they perceive their peers or social circles doing so, potentially adapting to fit in (Torous et al., 2021). Adoption is further encouraged if influential individuals endorse AI-VR system adoption. Hence

H3: Social Influence Positively impacts Behavioral intention to adopt an AI-VR system.

Perceived benefits refer to the advantages and value individuals associate with using an AI-VR system (Abramova & Böhme, 2016), particularly in terms of the potential for an enhanced user experience (Jensen & Konradsen, 2018). The more immersive and enjoyable the experience provided by the AI-VR system, the stronger the inclination to adopt (Lee & Kim, 2022). People expect technology to improve their competence, efficiency, and effectiveness (Venkatesh et al., 2012), leading to increased behavioral intention to adopt when they believe the AI-VR system can enhance their performance or help them achieve their goals (Rana et al., 2022). Individuals may also be motivated to adopt AI-VR systems by the perceived benefits of being associated with cutting-edge technological advancements. Hence

H4: Perceived Benefits of using an AI-VR System Positively impact Behavioral Intention to adopt the technology.

Technophobia refers to the anxiety or fear individuals experience when encountering new technologies (Khasawneh, 2020b), often stemming from unfamiliarity with the technology (Osiceanu, 2015). Those with technophobia may find AI-VR systems daunting or difficult to understand (Callaghan et al., 2009), leading to a negative attitude and reduced intention to use (Osiceanu, 2015). Concerns about technical aspects, user interface, or data security risks can further diminish trust in the technology and decrease adoption intent (Koul & Eydgahi, 2020). Fear of making mistakes or facing adverse consequences may also deter adoption (Khasawneh, 2018b), resulting in a generally negative relationship between technophobia and behavioral intention to use AI-VR systems. Hence

H5: Technophobia Negatively impacts Behavioral intention to adopt an AI-VR system.

Technological neophilia refers to the strong inclination towards adopting new technologies (Formatje, 2016), driven by enthusiasm and curiosity (Marius, 2014). Neophiles are often among the first to explore and utilize innovative solutions (Veryard, 2001), indicating their likelihood to adopt AI-VR systems early on to stay abreast of technological advancements. Their high level of technological neophilia is typically accompanied by a positive attitude towards technology (S.-M. Lee, 2015b), believing it enhances productivity and offers new opportunities (Hungate, 2018b). This positive outlook fuels their intention to implement AI-VR systems, recognizing technology as a valuable asset with numerous benefits.

H6: Technological Neophilia Positively impacts Behavioral intention to adopt an AI-VR system.

Media richness refers to a communication medium's ability to convey intricate information (Daft & Lengel, 1986b) shaping individuals' perceptions and behavioral intentions towards technology (Joseph Schmitz & Janet Fulk, 1991). AI-VR systems, offering immersive experiences, qualify as rich media (U. K. Lee, 2022b), providing extensive sensory input and interaction through virtual environments (Chen, 2022). Such immersive experiences positively influence adoption intentions (C. Y. Chen, 2022). Individuals are more inclined to adopt technology when they anticipate rich and engaging experiences (Dennis & Kinney, 1998b), as demonstrated through videos, demonstrations, and interactive presentations illustrating AI-VR system benefits (Maity et al., 2018). Media richness also relates to user feedback and interactivity, enhancing customer satisfaction (Hui et al., 2023). Positive user experiences, enabled by rich media and interactive features, bolster adoption intentions by conveying value and benefits (Hui et al., 2023).

H7: Media Richness Positively impacts Behavioral intention to adopt an AI-VR system.

3.2 Moderating Effects

Venkatesh et al. (2003) demonstrated that age and experience moderated the relationships between performance expectancy, effort expectancy, and social influence. No literary evidence shows that age or experience impact technophobia, technological neophilia, perceived benefits, or media richness. Therefore, in this study, in addition to the UTAUT variables, we evaluate the moderating effects of age and experience on these additional variables. Hence

H8a: Age Moderates the Impact of PE, EE, SI, Technophobia, Technological Neophilia, perceived Benefits and Media Richness on Behavioral Intention to Adopt AI-CRM

H8b: Work experience Moderates the Impact of PE, EE, SI, Technophobia, Technological Neophilia, perceived Benefits and Media Richness on Behavioral Intention to Adopt AI-CRM

3.3 3.3. Conceptual Model

Figure 1 depicts the conceptual research model based on the proposed hypotheses.

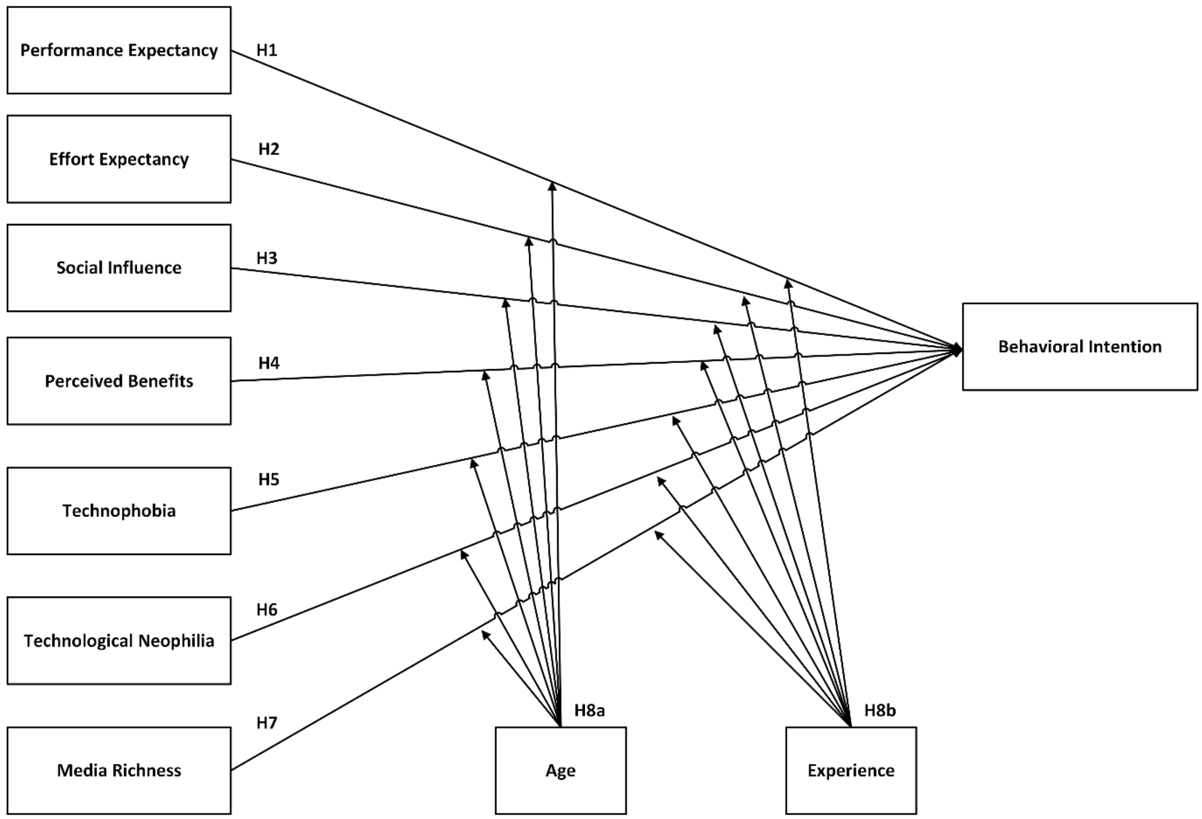

Figure 1 Conceptual model for direct impact of constructs on Behavioral intention to adopt AI-VR system.

4 Research Methodology.

4.1 Sample Size Determination

Daniel Soper's Sample Size Calculator for structural equation models, referencing Cohen (1987) and Soper (2023), was utilized to determine the sample size. Considering seven latent and 37 observed variables, an effect size of 0.3, power set at 0.9, and a significance threshold of 0.05, the calculator indicated a minimum sample size of 120 for the model structure and 232 for detecting the effect. To ensure robustness, a conservative minimum sample size of 350 was established after incorporating a safety factor of 50%.

4.2 Sampling Procedure

Purposive sampling was employed to ensure representation from sales executives of dealerships in Kolkata, West Bengal, India, focusing on the adoption of AI-VR systems in passenger cars. Sales executives from 27 showrooms, representing 11 manufacturers, participated in the study. This sampling method was chosen to address potential participation issues effectively and ensure representation of informed participants (Tongco, 2007).

4.3 Data Collection

Data collection was carried out between March and April 2023, involving visits to various dealerships where the authors personally administered the questionnaire to sales executives. The data collection process was conducted outside usual working hours to minimize disruption. A total of 435 surveys were distributed.

4.4 Data Filtering

A rigorous filtering process was implemented to maintain data integrity. Unfilled responses and those displaying a standard deviation below 0.25 were excluded. This resulted in a reliable dataset comprising 401 responses, surpassing the predefined cutoff threshold of 350.

4.5 Participant Characteristics

Participants had an average age of 30 years, with 22% holding graduate degrees and 77% postgraduate degrees. The average work experience was 6.4 years. Notably, 89% of respondents were already familiar with AI, while all participants were provided with a comprehensive introduction to ensure a foundational understanding.

4.6 Questionnaire Design

The survey instrument comprised two sections. The first section collected sociodemographic and occupational data, while the second section evaluated attitudes and perceptions regarding the acceptance of AI-VR systems based on the UTAUT framework. A 5-point Likert scale questionnaire was administered, taking participants approximately 20 minutes to complete.

5 Data analysis and results

5.1 Measurement Model

The study conducted reliability tests to evaluate the consistency of identified constructs. Cronbach's alpha was calculated for each construct (Chatterjee et al., 2020). All constructs exceeded the acceptable threshold of 0.6, indicating high internal consistency.

Factor loadings of each item were assessed, with a minimum acceptable value of 0.7 ((Barroso & Carri, 2010). Composite reliability (CR) was evaluated using Gefen & Straub's (2002) method, with a minimum acceptable CR of 0.7 (Urbach N., 2010). All constructs surpassed these thresholds, ensuring their dependability. For convergent validity, average variance extracted (AVE) was calculated (Fornell & Larcker F., 1981)). A minimum AVE of 0.5 was deemed acceptable (Hair, 2009), which all constructs exceeded, meeting convergent validity requirements.

Discriminant validity was assessed by comparing AVE with correlation coefficients (Fornell & Larcker, 1981). Additionally, the Heterotrait-Monotrait (HTMT) test (Henseler et al., 2014) was employed. All HTMT values were below 0.85, confirming discriminant validity (Voorhees et al., 2016)

Table 2: Test results for reliability, internal consistency, and convergent validity.

Latent and Observable Variables	λ	CR	α	AVE
Performance expectancy		0.872	0.805	0.631
PerEx1	0.85			
PerEx2	0.791			
PerEx3	0.807			
PerEx4	0.726			
Effort Expectancy		0.836	0.711	0.63
EffEx1	0.736			
EffEx4	0.813			
EffEx5	0.829			
Social Influence		0.858	0.751	0.669
SocInf1	0.752			
SocInf4	0.849			
SocInf5	0.848			
Percieved Benefit		0.862	0.786	0.609
PerBft1	0.774			
PerBft2	0.799			
Perbft3	0.8			
Perbft4	0.747			
Media Richness		0.877	0.824	0.588
MeRi1	0.728			
MeRi2	0.689			
MeRi4	0.793			
Meri5	0.799			
Meri6	0.818			
Technophobia		0.857	0.786	0.6

Latent and Observable Variables	**λ**	**CR**	**α**	**AVE**
TP1	0.728			
TP2	0.804			
TP3	0.741			
TP5	0.821			
Technological Neophilia				
TN1	0.708	0.79	0.704	0.557
TN4	0.718			
TN5	0.81			
Behavioral Intention		0.88	0.794	0.711
BevInt1	0.883			
BevInt2	0.877			
BevInt4	0.765			

λ=Factor Loadings; CR=Composite Reliability; α=Cronbach's Alpha; AVE=Average variance Extracted

Table 3: Fornell-Larker Criteria for Discriminant Validity

Construct	PerEx	EffEx	SocInf	PerBft	MeRi	TP	TN	BevInt
PerEx	**0.6313**							
EffEx	0.1149	**0.6300**						
SocInf	0.2584	0.0855	**0.6686**					
PerBft	0.3328	0.0955	0.1396	**0.6089**				
MeRi	0.2049	0.1829	0.1887	0.38	**0.5881**			
TP	0.0103	0.0201	0.0371	0.0019	0.1829	**0.6000**		
TN	0.2834	0.0517	0.2137	0.3128	0.189	0.0301	**0.5574**	
BevInt	0.3551	0.072	0.1778	0.3679	0.2785	0.0145	0.3115	**0.7111**

PerEx= performance Expectancy; EffEx= Effort Expectancy; SocInf=Social Influence; PerBft= Perceived Benefit; MeRi=Media Richness; TP=Technophobia; TN=Technological Neophilia; BevInt= Behavioral Intention

Table 4: HTMT ratio for Discriminant Validity

Construct	PerEx	EffEx	SocInf	Per	Me	TP	TN	BevInt
PerEx								
EffEx	0.451							
SocInf	0.6437	0.3854						
PerBft	0.7246	0.409	0.479					
MeRi	0.5556	0.5613	0.5441	0.7644				
TP	0.1158	0.1949	0.2394	0.0412	0.0119			
TN	0.7477	0.3264	0.6738	0.7992	0.6072	0.0053		
BevInt	0.7402	0.3499	0.5427	0.7677	0.6538	0.1397	0.7949	

5.2 Structural Model

The study utilized PLS-SEM with bootstrapping using SmartPLS4, employing 5000 resamples, to conduct a structural path analysis. This statistical technique allowed for the examination of relationships between latent variables and the assessment of their significance. By resampling the data multiple times, the study obtained reliable estimates of coefficients and assessed their significance without assuming normality. The resulting R^2 value of 0.5203 indicates that the independent variables explained approximately 52.03% of the variance in the dependent variable. This approach provided robust statistical analysis, considering the non-normal data distribution and smaller sample size.

4.4.1. Direct Impact

The table displays the outcomes of the direct impacts of latent components on Behavioral Intention.

Table 5: Bootstrap results for direct impact of latent constructs on Behavioral Intention to adopt AI-VR System.

Path	Hypothesis	β-value	T-value	p-value	Remarks
PerEx → BevInt	H1	0.2449	4.6152	0	Supported
EffEx → BevInt	H2	-0.0427	-0.961	0.3368	Not Supported
SocInf → BevInt	H3	0.0776	1.4226	0.1552	Not Supported
PerBft → BevInt	H4	0.2251	4.0779	0	Supported
MeRi → BevInt	H5	0.1771	2.9633	0.0031	Supported
TP → BevInt	H6	-0.1055	-2.458	0.0141	Supported
TN → BevInt	H7	0.1979	3.2529	0.0012	Supported

4.4.2. Moderation effects

Table lays down the results of the moderating effect of "Age" and experience between the latent constructs and Behavioral Intention.

Table 6 Moderating Effects of Age and Experience

Path	Hypothesis	β-value	t-value	p-value	Remarks
Age_PerEx → BevInt		-0.032	-0.679	0.4707	
Age_Effex →BevInt		0.0075	0.1398	0.8889	
Age_SocInf → BevInt		-0.059	-0.793	0.428	
Age_PerBft → BevInt	7a	-0.025	-0.45	0.6529	Not Supported
Age_MeRi → BevInt		-0.036	-0.689	0.4907	
Age_TP → BevInt		-0.003	-0.051	0.959	
Age_TN → BevInt		0.0319	0.5142	0.6072	
Exp_PerEx →BevInt		-0.032	-0.679	0.4707	
Exp_Effex → BevInt		0.0075	0.1398	0.8889	
Exp_SocInf → BevInt		-0.059	-0.793	0.428	
Exp_PerBft → BevInt	7b	-0.025	-0.45	0.6529	Not Supported
Exp_MeRi → BevInt		-0.036	-0.689	0.4907	
Exp_TP → BevInt		-0.003	-0.051	0.959	
Exp_TN → BevInt		0.0319	0.5142	0.6072	

6 Discussion

6.1 Direct Impact

The connection between believing in technology's ability to enhance performance and the intention to use it suggests that perceiving technology as a tool for improving efficiency increases the likelihood of adopting it. In essence, individuals who perceive technology as enhancing productivity are more inclined to adopt and incorporate it into their lives. This perception significantly boosts the tendency to adopt AI-CRM systems in the future. Those who believe in technology's potential to boost productivity are more likely to integrate it into their daily routines and professional activities. Conversely, the lack of a significant relationship between ease of use and intention to use suggests that the perceived simplicity of technology may not strongly influence people's willingness to adopt it. Other factors beyond ease of use may play a more significant role in their decision-making. Similarly, the limited impact of social influence on intention to indicates that the advice or opinions of others may not greatly sway individuals' attitudes toward technology adoption. Instead, personal factors such as individual views, perceptions, and experiences are likely to have a more significant impact.

The significant influence of perceived benefits on intention to use emphasizes the importance of recognizing advantages such as increased productivity and better interaction. Acknowledging these benefits serves as a motivating factor for individuals to adopt technology. Put simply, individuals are more likely to embrace technology when they perceive benefits such as productivity gains and improved communication. The positive relationship between media richness and behavioral intentions underscores the importance of engaging media formats in influencing technology adoption. Interactive media tends to capture attention and stimulate curiosity, fostering a desire to explore new technological advancements.

Furthermore, the study highlights an inverse relationship between technophobia and intention to use technology. Higher levels of technophobia are associated with decreased inclination to adopt technology. Conversely, there's a positive relationship between technological neophilia and intention to use technology. Individuals with a strong inclination toward embracing new technologies are more likely to engage with them. Those who possess traits associated with technological neophilia, such as curiosity and adaptability, are more motivated to integrate technology into their daily lives."

6.2 Moderation

This study examined the potential moderating effects of age and experience on behavioral intention. A moderator exerts an impact on the strength and dynamics of a relationship. Within this particular context, the study's objective was to ascertain whether the relationships between the examined variables might be modified or impacted by factors such as age and experience. Nevertheless, the study's results revealed that age and experience did not substantially impact modifying the intensity or characteristics of these associations. Across various age groups and experience levels, the influence of variables under study on behavioral intention exhibited consistent patterns. This suggests that the variables of age and experience did not exert any significant influence on how they interacted with behavioral intention.

To summarize, this study investigated the adoption of AI-VR systems in passenger car sales, particularly in the Indian market, utilizing the UTAUT framework extended with new factors. Results demonstrate that perceived performance expectancy, benefits, media richness, technological neophilia positively influence behavioral intention, while technophobia exhibits a negative impact. Age and experience did not significantly moderate these relationships. The findings highlight the importance of perceived benefits and technological inclination in driving AI-VR adoption, providing valuable insights for automakers and marketers to strategize effectively. This research contributes to understanding the complex dynamics of AI-VR adoption in the automotive industry.

7 Implications and Contributions

7.1 Managerial Implications

This study provides crucial insights for car dealership managers aiming to improve AI-VR adoption. Sales leaders' opinions of the technology's benefits are important since performance expectation and behavioral intention are positively correlated. Customized training, explicit AI-VR benefits, and technological support resources can help managers achieve this. Despite the lack of a correlation between effort expectancy and behavioral intention, managers should prioritize AI-VR system usability for simplicity and accessibility.

Social influence positively affects behavioral intention, suggesting dealerships should use social networks and prominent persons to promote AI-VR. Technology adoption can be boosted by important executives championing technology, peer support, and a tech-friendly culture. Promoting perceived benefits like better customer connection and sales conversions is key. Success stories can demonstrate AI-VR's sales benefits, helping sales leaders grasp technology adoption's worth.

Positive associations with technical neophilia underscore the need of encouraging innovation and curiosity. Managers can encourage learning, keep up with industry trends, and train sales executives in technical skills. Creating a technical neophilia environment, involving experimentation and recognition of new ideas, increases AI-VR adoption behavior.

The favorable connections between media richness and technological neophilia emphasize the importance of communication channel characteristics. Interactive virtual presentations and rich media can improve comprehension. Managers should assess communication needs and choose channels to enrich information and engagement, promoting AI-VR adoption.

Managers should emphasize perceived benefits, technology simplification, social influence, and technological neophilia. Sales executives' behavioral desire to use AI-VR technology will be maximized by effective communication, training, and an innovative atmosphere, ensuring successful integration in the competitive automotive industry.

7.2 Theoretical Contributions

This study significantly advances technology adoption research by expanding the Unified Theory of Acceptance and Use of Technology (UTAUT) framework and incorporating additional elements such as Technological Neophilia, Technophobia, Perceived Benefits, and Media Richness. This inclusion enriches the theoretical boundaries of UTAUT, offering a more comprehensive understanding of the factors influencing individuals' intentions to adopt and use new technology. By integrating UTAUT with social theories and media richness theory, this study provides a holistic theoretical framework, enhancing the nuanced comprehension of technology adoption.

The introduction of individual attributes such as technological neophilia and technophobia contributes to understanding how personal factors shape technology adoption. This study emphasizes the importance of considering psychological aspects and individual characteristics in technological acceptability research, shedding light on how qualities such as neophilia and technophobia impact attitudes and intentions toward technology adoption.

A notable original contribution is the introduction of Technological Neophilia as a construct, which captures individuals' predisposition to embrace new technology and novel experiences. This addition provides insight into the influence of natural curiosity and attraction to new technologies on behavioral intentions, contributing a new dimension to research on technology adoption.

The positive association between media richness and technological neophilia underscores the significance of communication channels in technology adoption. The findings suggest that media richness, characterized by cues, feedback, and interactivity, plays a crucial role in influencing people's willingness to adopt new technology. This extends the relevance of media richness theory to the context of technology adoption, broadening the understanding of communication dynamics in technological decision-making.

Challenging conventional wisdom, the positive relationship between technophobia and technological neophilia reveals that individuals fearful of new technologies may simultaneously harbor curiosity about them. This insight expands our understanding of the coexistence of fear and curiosity in human psychology, emphasizing the need to address both elements in technology adoption. Bridging the fear– curiosity gap is crucial for achieving more positive technology adoption outcomes, highlighting the theoretical implications of understanding these psychological elements in the adoption process.

5 Limitations and Future Research Directions

This study acknowledges several limitations that offer avenues for future research. The geographical focus on West Bengal may limit generalizability, prompting future investigations to encompass diverse locations or nations for enhanced external validity. The absence of AI-VR implementation in Indian dealerships constrained direct observation, prompting future research in industries where AI-VR is more prevalent. Unmeasured variables may confound associations, urging future studies to consider additional factors. Employing a cross-sectional approach, the study suggests that future research could adopt longitudinal designs to unravel temporal dynamics and changes in attitudes, intentions, and adoption behaviors over time.

6 Conclusion

This study expands upon the UTAUT paradigm by including four new variables (Technophobia, Technological Neophilia, Perceived Benefits, and Media Richness) to thoroughly investigate the adoption of AI-VR systems in car sales. Analyzed using PLS-SEM, data from 401 vehicle sales executives in Kolkata were examined through a questionnaire employing a 5-point Likert scale. The study finds crucial determinants that influence the adoption of AI-VR technology: Performance Expectancy has a favorable correlation with Behavioral Intention, although Effort Expectancy does not exhibit a meaningful link. Social Influence has no substantial effect on behavioral intention, although perceived benefits and technological neophilia exhibit strong connections. Technophobia is linked in a negative way with behavioral intention. This study explores the interconnections within the UTAUT paradigm and identifies favorable correlations between technological neophilia and performance expectancy, effort expectancy, media richness, and technophobia. Furthermore, there is a favorable correlation between social influence and technological neophilia. These findings provide guidance for implementing specific interventions in businesses, with a focus on aspects such as perceived advantages, fear of technology, and enthusiasm for new technology in promoting the use of AI-VR among sales leaders.

References

Abramova, S., & Böhme, R. (2016). Perceived benefit and risk as multidimensional determinants of bitcoin use: A quantitative exploratory study. *2016 International Conference on Information Systems, ICIS 2016*, *Zohar 2015*, 1–20. https://doi.org/10.17705/4icis.00001

Al-Adwan, A. S., Yaseen, H., Alsoud, A., Abousweilem, F., & Al-Rahmi, W. M. (2022). Novel extension of the UTAUT model to understand continued usage intention of learning management systems: the role of learning tradition. *Education and Information Technologies*, *27*(3), 3567–3593. https://doi.org/10.1007/s10639-021-10758-y

Barroso, C., & Carri, G. C. (2010). Handbook of Partial Least Squares. *Handbook of Partial Least Squares*, 427–447. https://doi.org/10.1007/978-3-540-32827-8

Chang, C. C., Liang, C., Chou, P. N., & Lin, G. Y. (2017). Is game-based learning better in flow experience and various types of cognitive load than non-game-based learning? Perspective from multimedia and media richness. *Computers in Human Behavior*, *71*, 218–227. https://doi.org/10.1016/j.chb.2017.01.031

Chatterjee, S., Ghosh, S. K., Chaudhuri, R., & Chaudhuri, S. (2020). Adoption of AI-integrated CRM system by Indian industry: from security and privacy perspective. *Information and Computer Security*, *29*(1), 1–24. https://doi.org/10.1108/ICS-02-2019-0029

Chatterjee, S., Rana, N. P., Khorana, S., Mikalef, P., & Sharma, A. (2021). Assessing Organizational Users' Intentions and Behavior to AI Integrated CRM Systems: a Meta-UTAUT Approach. *Information Systems Frontiers*, 1–15. https://doi.org/10.1007/S10796-021-10181-1/TABLES/3

Chaudhuri, R., Chatterjee, S., Ghosh, A., Vrontis, D., & Thrassou, A. (2022). Sustainable innovation for shared mobility: contextual and consumer factors of an Indian car subscription business model. *International Journal of Entrepreneurial Behaviour and Research*. https://doi.org/10.1108/IJEBR-01-2022-0090

Chen, C. Y. (2022). Immersive virtual reality to train preservice teachers in managing students' challenging behaviours: A pilot study. *British Journal of Educational Technology*, *53*(4), 998–1024. https://doi.org/10.1111/bjet.13181

Daft, R. L., & Lengel, R. H. (1986a). Organizational Information Requirements, Media Richness and Structural Design. *Management Science*, *32*(5), 554–571. https://doi.org/10.1287/mnsc.32.5.554

Daft, R. L., & Lengel, R. H. (1986b). Organizational Information Requirements, Media Richness and Structural Design. *Management Science*, *32*(5), 554–571. https://doi.org/10.1287/mnsc.32.5.554

De Oliveira, T. R., Rodrigues, B. B., Da Silva, M. M., Spinassé, R. A. N., Ludke, G. G., Gaudio, M. R. S., Gomes, G. I. R., Cotini, L. G., Da Silva Vargens, D., Schimidt, M. Q., Andreão, R. V., & Mestria, M. (2023). Virtual Reality Solutions Employing Artificial Intelligence Methods: A Systematic Literature Review. *ACM Computing Surveys*, *55*(10). https://doi.org/10.1145/3565020

Dennis, A. R., & Kinney, S. T. (1998a). Testing Media Richness Theory in the New Media: The Effects of Cues, Feedback, and Task Equivocality. *Information Systems Research*, *9*(3), 256–274. https://doi.org/10.1287/isre.9.3.256

Dennis, A. R., & Kinney, S. T. (1998b). Testing Media Richness Theory in the New Media: The Effects of Cues, Feedback, and Task Equivocality. *Information Systems Research*, *9*(3), 256–274. https://doi.org/10.1287/isre.9.3.256

Esmaeilzadeh, P. (2020). Use of AI-based tools for healthcare purposes: A survey study from consumers' perspectives. *BMC Medical Informatics and Decision Making*, *20*(1), 1–19. https://doi.org/10.1186/s12911-020-01191-1

Fan, W., Liu, J., Zhu, S., & Pardalos, P. M. (2020). Investigating the impacting factors for the healthcare professionals to adopt artificial intelligence-based medical diagnosis support system (AIMDSS). *Annals of Operations Research*, *294*(1–2), 567–592. https://doi.org/10.1007/S10479-018-2818-Y/FIGURES/3

Feng, X., Khemacheevakul, K., Siller, S. D. L., Wolodko, J., & Wismer, W. (2022). Effect of Labelling and Information on Consumer Perception of Foods Presented as 3D Printed. *Foods*, *11*(6). https://doi.org/10.3390/foods11060809

Formatje, N. B. (2016). *Neophilia, UOC (Universitat Oberta de Catalunya)*. https://www.uoc.edu/portal/en/news/actualitat/2016/175-neophile.html%0A%0A

Fornell, C., & Larcker F., D. (1981). CLAES FORNELL AND DAVID F. LARCKER* Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *XVIII*(February), 39–50.

FRICKER, P. (2019). Virtual Reality for Immersive Data Interaction. *Landscape Architecture Frontiers*, *7*(2), 153. https://doi.org/10.15302/j-laf-20190216

Gandedkar, N. H., Wong, M. T., & Darendeliler, M. A. (2021). Role of virtual reality (VR), augmented reality (AR) and artificial intelligence (AI) in tertiary education and research of orthodontics: An insight. *Seminars in Orthodontics*, *27*(2), 69–77. https://doi.org/10.1053/j.sodo.2021.05.003

Giordano, S., Clodoveo, M. L., Gennaro, B. De, & Corbo, F. (2018). Factors determining neophobia and neophilia with regard to new technologies applied to the food sector: A systematic review. *International Journal of Gastronomy and Food Science*, *11*(August 2017), 1–19. https://doi.org/10.1016/j.ijgfs.2017.10.001

Gong, Y. (2021). Application of virtual reality teaching method and artificial intelligence technology in digital media art creation. *Ecological Informatics*, *63*(January), 101304. https://doi.org/10.1016/j.ecoinf.2021.101304

Griffin, A. S., Netto, K., & Peneaux, C. (2017). Neophilia, innovation and learning in an urbanized world: a critical evaluation of mixed findings. *Current Opinion in Behavioral Sciences*, *16*, 15–22. https://doi.org/10.1016/j.cobeha.2017.01.004

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., Ketchen, D. J., Hair, J. F., Hult, G. T. M., & Calantone, R. J. (2014). Common Beliefs and Reality About PLS: Comments on Rönkkö and Evermann (2013). *Organizational Research Methods*, *17*(2), 182–209. https://doi.org/10.1177/1094428114526928

Ho, M. T., Mantello, P., Ghotbi, N., Nguyen, M. H., Nguyen, H. K. T., & Vuong, Q. H. (2022). Rethinking technological acceptance in the age of emotional AI: Surveying Gen Z (Zoomer) attitudes toward non-conscious data collection. *Technology in Society*, *70*(June), 102011. https://doi.org/10.1016/j.techsoc.2022.102011

Huang, Y. C. (2023a). Integrated concepts of the UTAUT and TPB in virtual reality behavioral intention. *Journal of Retailing and Consumer Services*, *70*(August 2022), 103127. https://doi.org/10.1016/j.jretconser.2022.103127

Huang, Y. C. (2023b). Integrated concepts of the UTAUT and TPB in virtual reality behavioral intention. *Journal of Retailing and Consumer Services*, *70*(August 2022), 103127. https://doi.org/10.1016/j.jretconser.2022.103127

Hui, X., Raza, S. H., Khan, S. W., Zaman, U., & Ogadimma, E. C. (2023). Exploring Regenerative Tourism Using Media Richness Theory: Emerging Role of Immersive Journalism, Metaverse-Based Promotion, Eco-Literacy, and Pro-Environmental Behavior. *Sustainability*, *15*(6), 5046. https://doi.org/10.3390/su15065046

Hungate, H. L. (2018a). *The Rearview Mirror and Windshield : Utilizing the Intersection of Nostalgia and Neophila to Target Today ' s Consumers "*.

Hungate, H. L. (2018b). *The Rearview Mirror and Windshield : Utilizing the Intersection of Nostalgia and Neophila to Target Today ' s Consumers "*.

Jain, M., & Kulkarni, P. (2022). Application of AI, IOT and ML for Business Transformation of The Automotive Sector. *2022 International Conference on Decision Aid Sciences and Applications, DASA 2022*, 1270–1275. https://doi.org/10.1109/DASA54658.2022.9765294

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577–586. https://doi.org/10.1016/J.BUSHOR.2018.03.007

Joseph Schmitz, & Janet Fulk. (1991). Organizational Colleagues, Media Richness, and Electronic Mail: A Test of the Social Influence Model of Technology Use. *Communication Research*.

Khasawneh. (2020). *Technical Knowledge and Ability Expectation Verses Reality the Dunning- Technical Knowledge and Ability : Expectation Verses Reality the Dunning-Kruger Effect*. *5*(August), 21–29.

Khasawneh, O. Y. (2018a). Technophobia: Examining its hidden factors and defining it. *Technology in Society*, *54*(December 2017), 93–100. https://doi.org/10.1016/j.techsoc.2018.03.008

Khasawneh, O. Y. (2018b). Technophobia without boarders: The influence of technophobia and emotional intelligence on technology acceptance and the moderating influence of organizational climate. *Computers in Human Behavior*, *88*(July), 210–218. https://doi.org/10.1016/j.chb.2018.07.007

Khasawneh, O. Y. (2022). Technophobia: How Students' Technophobia Impacts Their Technology Acceptance in an Online Class. *International Journal of Human-Computer Interaction*. https://doi.org/10.1080/10447318.2022.2085398

Koul, S., & Eydgahi, A. (2020). The impact of social influence, technophobia, and perceived safety on autonomous vehicle technology adoption. *Periodica Polytechnica Transportation Engineering*, *48*(2), 133–142. https://doi.org/10.3311/PPtr.11332

Kumari, S., Raghuram, P., Venkatesh, V. G., & Shi, Y. (2022). Future perspectives on progressive farming with adoption of virtual reality technology for sustainable quality in agriculture. *TQM Journal*, *34*(2), 250–279. https://doi.org/10.1108/TQM-06-2021-0191

Lee, S.-M. (2015a). *Curiosity and Experience Design: Developing the Desire to Know and Explore in Ways That Are Sociable, Embodied, and Playful*. 371.

Lee, S.-M. (2015b). *Curiosity and Experience Design: Developing the Desire to Know and Explore in Ways That Are Sociable, Embodied, and Playful*. 371. http://hdl.handle.net/1842/20977

Lee, U. K. (2022a). Tourism Using Virtual Reality: Media Richness and Information System Successes. *Sustainability (Switzerland)*, *14*(7). https://doi.org/10.3390/su14073975

Lee, U. K. (2022b). Tourism Using Virtual Reality: Media Richness and Information System Successes. *Sustainability (Switzerland)*, *14*(7). https://doi.org/10.3390/su14073975

Lee, U. K., & Kim, H. (2022). UTAUT in Metaverse: An "Ifland" Case. *Journal of Theoretical and Applied Electronic Commerce Research*, *17*(2), 613–635. https://doi.org/10.3390/jtaer17020032

Liu, S. H., Liao, H. L., & Pratt, J. A. (2009). Impact of media richness and flow on e-learning technology acceptance. *Computers and Education*, *52*(3), 599–607. https://doi.org/10.1016/j.compedu.2008.11.002

Loske, D., & Klumpp, M. (2021). Intelligent and efficient? An empirical analysis of human–AI collaboration for truck drivers in retail logistics. *International Journal of Logistics Management*, *32*(4), 1356–1383. https://doi.org/10.1108/IJLM-03-2020-0149/FULL/PDF

Maity, M., Dass, M., & Kumar, P. (2018). The impact of media richness on consumer information search and choice. *Journal of Business Research*, *87*(February), 36–45. https://doi.org/10.1016/j.jbusres.2018.02.003

Marius, M. (2014). *Is technology spawning a generation of neophiles? | ICT Pulse – The leading technology blog in the Caribbean*. https://www.ict-pulse.com/2014/06/technology-spawning-generation-neophiles/

McClure, P. K. (2018). "You're Fired," Says the Robot: The Rise of Automation in the Workplace, Technophobes, and Fears of Unemployment. *Social Science Computer Review*, *36*(2), 139–156. https://doi.org/10.1177/0894439317698637

Meyer-Waarden, L., & Cloarec, J. (2022). "Baby, you can drive my car": Psychological antecedents that drive consumers' adoption of AI-powered autonomous vehicles. *Technovation*, *109*, 102348. https://doi.org/10.1016/J.TECHNOVATION.2021.102348

Mnyakin, M. (2020). Investigating the Impacts of AR, AI, and Website Optimization on Ecommerce Sales Growth. *ResearchBerg Review of Science and Technology*, *3*(1), 116–130. https://www.researchberg.com/index.php/rrst/article/view/89%0Ahttps://www.researchberg.com/index.php/rrst/article/download/89/91

Mukherjee, A., Pal, P., & Goswami, R. (2013). Facilitating Trade and Improving Competitiveness through Improved Road Network: Issues and Way Forward. *Foreign Trade Review*, *48*(2), 247–254. https://doi.org/10.1177/0015732513481239

Oncioiu, I., & Priescu, I. (2022). The Use of Virtual Reality in Tourism Destinations as a Tool to Develop Tourist Behavior Perspective. *Sustainability (Switzerland)*, *14*(7), 1–15. https://doi.org/10.3390/su14074191

Oreg, S. (2003). Resistance to change: Developing an individual differences measure. *Journal of Applied Psychology*, *88*(4), 680–693. https://doi.org/10.1037/0021-9010.88.4.680

Osiceanu, M.-E. (2015). Psychological Implications of Modern Technologies: "Technofobia" versus "Technophilia." *Procedia - Social and Behavioral Sciences*, *180*(November 2014), 1137–1144. https://doi.org/10.1016/j.sbspro.2015.02.229

Rana, J., Gaur, L., Singh, G., Awan, U., & Rasheed, M. I. (2022). Reinforcing customer journey through artificial intelligence: a review and research agenda. *International Journal of Emerging Markets*, *17*(7), 1738–1758. https://doi.org/10.1108/IJOEM-08-2021-1214

Stanica, I., Dascalu, M. I., Bodea, C. N., & Bogdan Moldoveanu, A. D. (2018). VR Job Interview Simulator: Where Virtual Reality Meets Artificial Intelligence for Education. *2018 Zooming Innovation in Consumer Technologies Conference, ZINC 2018*, 9–12. https://doi.org/10.1109/ZINC.2018.8448645

Theissler, A., Pérez-Velázquez, J., Kettelgerdes, M., & Elger, G. (2021). Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry. *Reliability Engineering and System Safety*, *215*, 107864. https://doi.org/10.1016/j.ress.2021.107864

Tongco, M. D. C. (2007). Purposive sampling as a tool for informant selection. *Ethnobotany Research and Applications*, *5*, 147–158. https://doi.org/10.17348/era.5.0.147-158

Torous, J., Bucci, S., Bell, I. H., Kessing, L. V., Faurholt-Jepsen, M., Whelan, P., Carvalho, A. F., Keshavan, M., Linardon, J., & Firth, J. (2021). The growing field of digital psychiatry: current evidence and the future of apps, social media, chatbots, and virtual reality. *World Psychiatry*, *20*(3), 318–335. https://doi.org/10.1002/wps.20883

Urbach N., & Ahlemann. F. (2010). Structural Equation Modeling in Information Systems Research Using Partial Least Squares. *Journal of Information Technology Theory and Application JITTA*, *11*(2), 5–40.

Vasconcelos, H., Jörke, M., Grunde-McLaughlin, M., Gerstenberg, T., Bernstein, M., & Krishna, R. (2022). *Explanations Can Reduce Overreliance on AI Systems During Decision-Making*. *7*(April), 1–38. https://doi.org/10.1145/3579605
Venkatesh, V. (2022). Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1–2), 641–652. https://doi.org/10.1007/s10479-020-03918-9
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003a). User acceptance of information technology: Toward a unified view. *MIS Quarterly: Management Information Systems*, *27*(3), 425–478. https://doi.org/10.2307/30036540
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003b). User acceptance of information technology: Toward a unified view. *MIS Quarterly: Management Information Systems*, *27*(3), 425–478. https://doi.org/10.2307/30036540
Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly: Management Information Systems*, *36*(1), 157–178. https://doi.org/10.2307/41410412
Veryard, R. (2001). *New Technology - Same Old Story*. http://www.users.globalnet.co.uk/~rxv/tcm/neophilia.htm
Vimalkumar, M., Sharma, S. K., Singh, J. B., & Dwivedi, Y. K. (2021). 'Okay google, what about my privacy?': User's privacy perceptions and acceptance of voice based digital assistants. *Computers in Human Behavior*, *120*, 106763. https://doi.org/10.1016/J.CHB.2021.106763
Voorhees, C. M., Brady, M. K., Calantone, R., & Ramirez, E. (2016). Discriminant validity testing in marketing: an analysis, causes for concern, and proposed remedies. *Journal of the Academy of Marketing Science*, *44*(1), 119–134. https://doi.org/10.1007/s11747-015-0455-4
Xu, M., Du, H., Niyato, D., Kang, J., Xiong, Z., Mao, S., Han, Z., Jamalipour, A., Kim, D. I., Xuemin, Shen, Leung, V. C. M., & Poor, H. V. (2023). *Unleashing the Power of Edge-Cloud Generative AI in Mobile Networks: A Survey of AIGC Services*. 1–39.