Quo Vadis Smart Cities? Exploring Citizen Adoption of AI-Driven Smart Mobility and Smart Home Technologies – a review on existing research

Sinu Thirukketheeswaran
Toulouse School of Management
LARS MEYER-WAARDEN
Marc Kuhn
Baden-Wuerttemberg Cooperative State University Stuttgart

Cite as:
Thirukketheeswaran Sinu, MEYER-WAARDEN LARS, Kuhn Marc (2025), Quo Vadis Smart Cities? Exploring Citizen Adoption of AI-Driven Smart Mobility and Smart Home Technologies – a review on existing research. *Proceedings of the European Marketing Academy*, 54th, (125947)

Paper from the 54th Annual EMAC Conference, Madrid, Spain, May 25-30, 2025

Quo Vadis Smart Cities? Exploring Citizen Adoption of AI-Driven Smart Mobility and Smart Home Technologies – a review on existing research

Abstract:

As smart cities evolve rapidly, fueled by advancements in artificial intelligence and internet of things, smart mobility and smart home technologies are becoming integral to urban living. However, factors influencing citizen adoption in these environments remain insufficiently explored. Our systematic literature review, guided by PRISMA and an extended TCCM framework, identifies a critical gap in understanding how AI-driven personalization and experiential factors, such as user interactions in smart environments, influence adoption. Findings reveal that current research predominantly focuses on rational drivers, overlooking psychological aspects and the role of artificial intelligence in scenarios like personalization or ride-hailing. Additionally, artificial intelligence is often viewed as a technological advancement rather than a driver of user-centric adoption factors. This review emphasizes the need for a holistic approach to address the complexity of citizen adoption and provides key insights for researchers and policymakers aiming to develop more effective strategies for integrating smart mobility and home technologies into urban lifestyles.

Keywords: Artificial Intelligence, Smart Home, Smart Mobility, TCCM

Track: Innovation Management & New Product Development

1. Introduction

The concept of smart cities is rapidly evolving, driven by advancements in smart energy, economy, homes, and mobility. "Smart" broadly refers to Internet of Things (IoT) and artificial intelligence (AI) devices and applications, including smart home technologies like voice assistants and lighting systems (Sepasgozar, Hawken, Sargolzaei, and Foroozanfa, 2019). Smart homes and mobility systems have recently gained attention in academia and marketing. This review examines citizen adoption of these technologies, emphasizing their potential for efficient, adaptable environments (Heinen, 2016; Marikyan, Papagiannidis, Rana, and Ranjan, 2023). AI, replicating human intelligence, is central to their functionality (Qin & Jiang, 2019). Smart mobility solutions, including autonomous vehicles and adaptive transit, improve safety, efficiency, and convenience but face barriers like trust and psychological readiness (Akram, Lavuri, and Mathuri, 2024; Gkartzonikas, Losada-Rojas, Christ, Pyrialakou, and Gkritza, 2023). Smart homes utilize AI for energy efficiency, comfort, and security but struggle with adoption challenges such as privacy concerns (Schill, Godefroit-Winkel, Diallo, and Barbar, 2019; Marikyan et al., 2023). Overcoming these barriers is essential to fully leverage AI's potential in advancing smart home and mobility adoption (Agatz, Erera, Savelsbergh, and Wang, 2021).

Existing literature (Marikyan et al., 2019; Becker & Axhausen, 2017; Butler, Yigitcanlar, and Paz, 2020) highlights a gap in synthesized insights on citizen adoption of smart technologies. While AI is acknowledged, its role in driving acceptance remains underexplored. This review seeks to address this gap by examining factors influencing citizen adoption of AI-enhanced smart mobility and smart home technologies through three core research questions (RQ):

RQ1: What are the existing and emerging thematic trends underlying citizen adoption of AI-enhanced smart mobility and smart home technologies?
RQ2: What are the most prevalent theories, methodologies, contexts and characteristics in the existing literature on citizen adoption of AI-enhanced smart mobility and smart home technologies, including both AI's influence as a driver and general adoption factors?
RQ3: What research directions should be pursued to advance the literature on citizen adoption of AI-enhanced smart mobility and smart home technologies?

To adress these RQs, this review applies a systematic methodology following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol for transparency (Moher, Liberati, Tetzlaff, Altman, and PRISMA Group*, 2009). Additionally, it employs an extended TCCM (xTCCM) framework, which integrates theories, contexts, characteristics, methods, measured effects, and limitations from existing research (Paul & Rosado-Serrano, 2019). This structured approach offers a comprehensive view of thematic clusters, critical factors affecting AI adoption, and future research directions in smart mobility and smart home technologies.

This paper is structured as follows: Section two outlines the methodology. Sections three and four present findings on publication trends and network relationships. Section five applies the xTCCM framework to classify research on AI-driven smart mobility and home adoption. The final sections propose future research directions and summarize key insights.

2. Review approach and structure

2.1 Article selection process

The review employs the PRISMA protocol (Moher et al., 2009) to identify relevant studies on smart mobility and smart home adoption. Using topic modeling and keyword co-occurrence networks, it develops a repeatable search strategy. Topic modeling, an unsupervised machine learning method, uncovers themes by analyzing word co-occurrences (Berger et al., 2020). The review protocol is shown in Fig. 1.

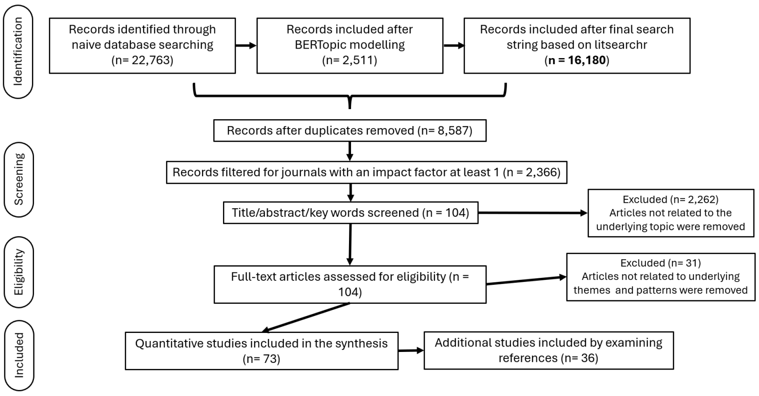

Figure 1: Methodology for Data Collection following PRISMA Guidelines

In the identification stage, a structured three-step approach was used to refine the search strategy for themes related to AI-enhanced smart mobility and smart home adoption. The process began with 23 targeted naive searches in the Web of Science and Scopus databases, covering terms like Smart City, Smart Living, Smart Homes, AI Mobility, Urban IoT, Smart City Adoption and Smart Home Acceptance. From these searches, all available literature since each term's earliest publication was extracted, yielding 22,763 publications after duplicate removal. Journals were not filtered initially as a larger text corpus supports the upcoming machine learning model's effectiveness in identifying thematically relevant topics and constructing a final search string (Alghamdi & Alfalqi, 2015). Next, we applied topic modeling using BertTopic, a transformer-based machine learning model (Grootendorst, 2022), categorizing articles into fields like Business, Social Sciences, and Psychology. This technique identified core themes across 2,511 articles, with BertTopic providing more nuanced insights than traditional methods like Latent Dirichlet Allocation (LDA). It quickly highlighted themes like “Technological Innovations for Assisted Living” and “Consumer Perceptions of Technology-Based Systems” (Egger & Yu, 2022). Of the 161 topics generated, 26 were deemed highly relevant by analyzing each topic’s top 5 documents and most frequent words, creating a refined dataset with complete metadata (authors, abstracts, etc.) for each article, resulting in 2,511 records. Finally, using the litsearchr tool in R, we refined search terms based on keyword co-occurrence (Grames, Stillman, Tingley, and Elphick, 2019). This generated the final search strings for AI-enhanced smart mobility adoption: *((TITLE-ABS-KEY ("autonomous vehicle" OR "intelligent transport" OR "public transport" OR "smart mobility" OR "smart transportation" OR "transport system" OR "systematic literature review" OR "urban mobility" OR "urban transport") AND TITLE-ABS-KEY ("acceptance model" OR "factors influencing" OR "future research" OR "technology acceptance")) and for AI-enhanced smart home adoption: (TITLE-ABS-KEY ("older adults" OR "smart homes" OR "smart technologies") AND TITLE-ABS-KEY ("acceptance model" OR "factors influencing" OR "future research" OR "technology acceptance"))*. This final dataset from the identification phase consisted of 16,180 records.

The screening stage applied strict inclusion and exclusion criteria to ensure relevance and rigor. After removing duplicates, 8,587 articles remained. Excluding conference proceedings, books, and chapters reduced the dataset to 2,366 journal articles with an impact factor ≥1. GPT-4 assisted in categorizing titles and abstracts using predefined keywords, identifying 104 thematic articles (2011–2024). This supervised approach ensured transparency and avoided "hallucination", ensuring transparency and adherence to scientific standards.

At the eligibility stage, full texts were reviewed, retaining 73 articles while excluding those with incidental mentions of smart mobility or home adoption. Snowball sampling added 36 studies, resulting in 109 papers selected for analysis on AI-enhanced smart mobility and home adoption.

2.1 Method of analysis

Systematic literature reviews, like the one conducted here, can risk misquotations and misinterpretations (Stang et al., 2018). For instance, the Newcastle-Ottawa Scale (NOS) has been misquoted in research (Luchini, Stubbs, Solmi, and Veronese, 2017). To ensure accuracy, we employ a multimodal Retrieval-Augmented Generation (RAG) method and manual data extraction (Salemi & Zamani, 2024). This process involves two steps: first, a multimodal LLM (e.g., GPT-4) extracts numerical, textual, and visual data into a controlled database (Yin et al., 2023), eliminating "hallucinations" by restricting outputs to curated content. Second, the LLM uses RAG answer queries based on indexed data, including accurate references from each paper (Chang, 2023). Prompts were crafted according to recent prompt engineering guidelines (Arvidsson & Axell, 2023), and all outputs were manually verified through iterative random sampling for reliability.

3. Identified theories

Research on smart home and smart mobility adoption uses various theoretical frameworks, grouped by psychological or rational constructs: behavioral intention and attitude-based theories, trust and risk-based theories, and personality and social norms-based theories. The behavioral intention and attitude-based theories group is the most prominent, with the Technology Acceptance Model (TAM) applied in 13% of studies (e.g. Park, Cho, Han, and Kwon, 2017), followed by the Theory of Planned Behavior (TPB) at 9.2% (e.g. Li, Kaye, Afghari, and Oviedo-Trespalacios, 2023) and UTAUT at 6.4% (e.g. Rahman, Deb, Strawderman, Burch, and Smith, 2019). In trust and risk-based theories, Trust Theory appears in 11% of studies (e.g. Kaur & Rampersad, 2018), while Risk Perception Theory accounts for 5.5% (e.g. Dixon, Hart, Clarke, O'Donnell, and Hmielowski, 2020).The personality and social norms-based theories group, also representing 11% of studies, focuses on personality traits, social influence, and self-identity (e.g. Heinen, 2016). Some studies also integrate multiple theories, especially relationally focused ones. The following sections explore these theory groups and less commonly used frameworks in smart technology adoption research.

4. Context

The xTCCM framework in this review examines the contextual dimensions of countries and industries. Findings for countries are based on 176 studies from 109 empirical articles. Since some studies span multiple countries, the total count of countries exceeds the number of articles. For industry analysis, only the primary industry investigated in each empirical article was considered.

Our analysis of smart home and mobility adoption highlights distinct research focuses across sectors and regions. In smart mobility, 45 papers (41.3%) focus on transportation and urban sustainability (e.g., Lee & Wong, 2021), and 23 papers (21.1%) examine automotive innovations like connectivity and electric vehicles (e.g., Hohenberger, Spörrle, and Welpe, 2017). Smart home adoption research, covered in 22 papers (20.2%), explores automation and connected devices such as smart thermostats and security systems (e.g., Marikyan et al., 2021). Smaller contributions include healthcare (1.8%), tourism (2.8%), residential services (1.8%), and retail (2.8%), highlighting diverse applications of IoT (e.g., Chang & Chen, 2021). Geographically, Asia leads with 29.5% of studies, focusing on smart cities (e.g., Chang & Chen, 2021), followed by Europe (24.4%) with sustainability as a key theme, and the U.S. (14.7%), emphasizing consumer behavior (e.g., Bansal & Kockelman, 2018). Australia (10.2%) addresses sustainability challenges, while 3.7% of studies lack specific geographic focus, signaling a gap for future research (e.g., Aldossari & Sidorova, 2020).

5. Characteristics

Key independent variables influencing adoption include user-related factors like perceived usefulness (31.2%) and ease of use (28.4%), which drive adoption of user-friendly technologies (Davis, 1989; Venkatesh & Davis, 2000). Privacy concerns (22.9%) and trust (17.4%) also play significant roles, with data security fears deterring users (Choi & Ji, 2015). Technology-related factors include performance expectancy (12.8%) and compatibility (4.6%), reflecting functionality and fit with users' routines (Moore & Benbasat, 1991). Contextual factors, such as social influence (14.7%), highlight peer and societal pressures on behavior (Fishbein & Ajzen, 2010; Venkatesh, Thong, and Xu, 2012). These variables illustrate the interplay of psychological, technological, and societal influences on adoption.

In examining mediating variables in smart mobility and smart home adoption, studies primarily identify user-related mediators like trust (18.3%) and perceived usefulness (17.4%). Trust serves as a key link between perceived risks and adoption outcomes (Choi & Ji, 2015), while perceived usefulness mediates between ease of use and final adoption (Davis, 1989). Attitude (9.2%) also plays a role, shaping adoption behaviors through social norms and perceived risks (Fishbein & Ajzen, 1975). Other user-related mediators include psychological factors (9.2%), such as emotional attachment, well-being and hedonic value (5.5%), which enhances enjoyment and engagement with smart technologies (Voss, Spangenberg, and grohmann, 2003). Technology-related mediators are less common but significant, with perceived value (3.7%) balancing expected benefits against costs (Venkatesh et al., 2012) and utilitarian value (3.7%) highlighting practical benefits like efficiency (Fauzi & Sheng, 2021). Satisfaction (2.8%) mediates between performance expectations and continued use (Al Haddad et al. 2020), while perceived risk and behavioral control (both 2.8%) moderate the impact of initial concerns and control on adoption decisions (Chen & Chao, 2011).

Moderating variables significantly shape smart mobility and smart home adoption by affecting the influence of factors like perceived usefulness and trust. User-related moderators such as socioeconomic characteristics (28.4%)—including income and education—impact adoption likelihood, with higher socioeconomic users more inclined to adopt due to affordability and tech familiarity (Tirado-Morueta, Aguaded-Gómez, and Hernando-Gómez, 2018). Gender (22.9%) and age (20.2%) also play critical roles, with men and younger users more likely to adopt smart technologies, while older users may resist due to complexity or privacy concerns (Baudier, Ammi & Deboeuf-Rouchon 2020). Contextual moderators include Technological Readiness (12.8%), reflecting users' and environments' preparedness for tech adoption (Blut & Wang, 2020), and Social Factors (3.7%), where peer and social network support boost confidence and adoption willingness (Fishbein & Ajzen, 2010).

In examining dependent variables, four main categories emerged: behavioral outcomes, perceptual and cognitive evaluations, value perceptions, and social influences. Behavioral outcomes, primarily adoption and usage intentions (74.3%), dominate research, reflecting their central role (Fishbein & Ajzen, 1975; Venkatesh, Morris, Davis, and Davis, 2003). Perceptual and cognitive evaluations, including perceived ease of use (24.8%), attitude (18.3%), and trust (10.1%), highlight ease, perspective, and reliability as adoption factors (Davis, 1989; Pavlou, 2003). Value perceptions focus on hedonic and utilitarian value, with some attention to functional and emotional benefits (Venkatesh et al., 2012). Social influences (1.8%) through subjective norms reflect societal pressure on user decisions (Fishbein & Ajzen, 2010).

Key factors influencing smart mobility and smart home adoption include performance expectancy, effort expectancy, social influence, and attitude, which shape user intentions (Moriuchi, 2023; Park et al., 2017). Demographics like income and education moderate these effects, while trust boosts adoption intent, and privacy concerns hinder it (Choi & Ji, 2015). Hedonic motivation and innovativeness drive early adoption, particularly for consumer technologies (Moriuchi, 2023). Perceived value, balancing benefits and costs, strongly impacts adoption and continued use (Venkatesh et al., 2012). Economic factors like willingness to pay and environmental concerns influence decisions, especially for green technologies (Ahn et al., 2016). Perceived control and risk perceptions are critical for autonomous vehicles (Hegner et al., 2019), while social norms and trust in institutions shape broader adoption. However, privacy concerns and regulatory issues remain barriers (Kaur & Rampersad, 2018).

6. Methods and limitations

When it comes to the method of data collection, survey methods dominated data collection, used in 94.5% of studies (103 articles). Online surveys were most common, appearing in 37 cases (33.9%) (e.g., Hohenberger et al., 2017), followed by on-site surveys (9 instances, 8.3%) (e.g., Deng et al., 2024) and simulation-based data collection (6 instances, 5.5%) (e.g., Rahman et al., 2017).

Analytical methods varied by data type and context. Structural Equation Modeling (SEM) was the most frequent, used in 62 studies (56.8%) to analyze latent variables and complex interrelationships (e.g., Park et al., 2017; Aldossari & Sidorova, 2020). Regression Analysis appeared in 19 studies (17.4%) to examine factors like user satisfaction and ease of use (e.g., Heinen, 2016; Rezaei & Caulfield, 2020). Other methods included Confirmatory Factor Analysis (9 instances, 8.3%) and Structural Topic Modeling (3 instances, 2.7%) for qualitative trend analysis (e.g., Rahman et al., 2019). Less common techniques were Logit Models (3 instances, 2.7%) (e.g., Saeed, Burris, Labi, and Sinha, 2020), Monte Carlo Simulations (1 instance, 0.9%) for accident modeling (e.g., Zhu & Tasic, 2021), Generalized Linear Models (2 instances, 1.8%), ANOVA (1 instance, 0.9%), and Spearman Correlation (4 instances, 3.6%) to explore variable relationships like intention to use and perceived ease of use.

Coming to the limitations, smart mobility and smart home adoption research, authors often report limitations that affect reliability. Generalizability, mentioned 78 times, is a key issue, as studies often focus on specific groups, like urban or tech-savvy users, limiting broader applicability (Hohenberger et al., 2017). Sampling biases, noted 73 times, arise from convenience sampling, while self-reported data, used in 36 studies, risks over-reporting positive behaviors (Akram et al., 2024). A narrow focus on variables, cited 31 times, overlooks factors like environmental attitudes, leading to incomplete insights (Bennett et al., 2020). Cross-sectional data mentioned 21 times, limits understanding of long-term behavioral changes (Akram et al., 2024). Demographic and geographical biases—cited in 9 and 2 studies, respectively—often overrepresent younger, urban users, neglecting diverse populations (Dirsehan & Can, 2019). Other issues include hypothetical scenarios (6 mentions) that lack real-world relevance (Benlian et al., 2020), non-confirmed effects (3 mentions) requiring validation (Chang & Chen, 2021), and broad scopes (3 mentions) that dilute analysis depth (Daziano, Sarrias, and Leard, 2017). Studies on specific product categories (3 mentions) (Bansal & Kockelmann, 2018) or using driving simulators (3 mentions) fail to capture real-world complexity (Buckley, Kaye, and Pradhan, 2018).

7. Future research agenda

Building on our review, we propose a research agenda with five key directions to advance AI-enhanced smart mobility and smart home adoption. These directions are derived from our findings across theoretical, contextual, characteristic, and methodological dimensions (see Table 1) and emphasize practical applications aligned with the research priorities of the Marketing Science Institute (MSI, 2024).

Theory. Research on AI adoption in smart homes and mobility often relies on rational models like UTAUT and TAM, limiting their ability to fully explain user acceptance (Iqbal & Idrees, 2022; Marikyan et al., 2024; Park et al., 2017). Expanding frameworks to include emotional and psychological theories, such as regulatory focus theory and emotional theories of risk and reward, can provide deeper insights into how emotions and motivations shape user behavior (Higgins, 1997). Combining trust and personality-based theories with traditional models could also enhance understanding of how AI personalization, such as adaptive pricing and entertainment features, influences acceptance.

Context. Future research should broaden its scope to diverse settings for AI-enhanced mobility and homes. Current studies focus on urban autonomous vehicles for navigation and control (Lee & Wong, 2021; Liu et al., 2019), but personalization in ride-hailing, adaptive pricing, and in-vehicle entertainment remains underexplored (Bansal & Kockelmann, 2018; Hohenberger et al., 2017). Expanding to urban-rural comparisons, cross-country studies, and domains like healthcare and tourism could reveal differences in adoption. In smart homes, cross-cultural research could address variations in privacy, trust, and expectations, guiding localized AI applications.

Characteristics. Characteristics. Research on AI adoption has focused heavily on rational factors, overlooking emotional and experiential dimensions. Future studies should integrate user experience, personalization preferences, and trust as key adoption factors (Meyer-Waarden & Cloarec, 2022; Puntoni et al., 2020). For smart mobility, this includes AI-driven personalization in ride-hailing and pricing; for smart homes, it involves AI tailoring tasks like health tracking and entertainment. Emotional impacts can be studied using tools like electroencephalogram (EEG) and wearable emotion trackers, offering real-time insights into user satisfaction and acceptance (Kuhn, Reit, Schwing, and Selinka, 2024).

Methods. Comprehensive, mixed-method approaches are needed to explore AI-enhanced smart mobility and home solutions. Longitudinal studies can track acceptance over time, while combining quantitative (e.g., surveys, simulations) and qualitative methods (e.g., interviews, ethnography) provides a complete view of user experiences (Meyer-Waarden &

Cloarec, 2022). Real-world experiments, industry collaborations, and tools like EEG and wearable devices capture emotional and experiential factors. Pilot programs with diverse stakeholders improve generalizability across contexts.

Main references

Agatz, N., Erera, A. L., Savelsbergh, M. W., & Wang, X. (2011). Dynamic ride-sharing: A simulation study in metro Atlanta. *Procedia-Social and Behavioral Sciences, 17*, 532-550.

Becker, F., & Axhausen, K. W. (2017). Literature review on surveys investigating the acceptance of automated vehicles. *Transportation, 44*(6), 1293-1306.

Butler, L., Yigitcanlar, T., & Paz, A. (2021). Factors influencing public awareness of autonomous vehicles: Empirical evidence from Brisbane. *Transportation research part F: traffic psychology and behaviour, 82*, 256-267.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley Publishing Company, Inc.

Gkartzonikas, C., Losada-Rojas, L. L., Christ, S., Pyrialakou, V. D., & Gkritza, K. (2023). A multi-group analysis of the behavioral intention to ride in autonomous vehicles: evidence from three US metropolitan areas. *Transportation, 50*(2), 635-675.

Heinen, E. (2016). Identity and travel behaviour: A cross-sectional study on commute mode choice and intention to change. *Transportation Research Part F: Traffic Psychology and Behaviour, 43*, 238–253.

Hohenberger, C., Spörrle, M., & Welpe, I. M. (2017). Not fearless, but self-enhanced: The effects of anxiety on the willingness to use autonomous cars depend on individual levels of self-enhancement. *Technological Forecasting and Social Change, 116*, 40-52.

Kaur, K., & Rampersad, G. (2018). Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars. *Journal of Engineering and Technology Management, 48*, 87-96.

Kim, Y., Park, Y., & Choi, J. (2017). A study on the adoption of IoT smart home service: using Value-based Adoption Model. *Total Quality Management & Business Excellence, 28*(9-10), 1149-1165.

Kuhn, M., Reit, V., Schwing, M., & Selinka, S. (2024). “Let the Driver off the Hook?” moral decisions of autonomous cars and their impact on consumer well-being. *Transportation Research Part A: Policy and Practice, 189*, 104224.

Marikyan, D., Papagiannidis, S., F. Rana, O., & Ranjan, R. (2024). Working in a smart home environment: examining the impact on productivity, well-being and future use intention. *Internet Research, 34*(2), 447-473.

Meyer-Waarden, L., Cloarec, J., Adams, C., Aliman, D. N., & Wirth, V. (2021). Home, sweet home: How well-being shapes the adoption of artificial intelligence-powered apartments in smart cities. *Systèmes d’information et management, 26*(4), 55-88.

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.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group*, T. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *Annals of internal medicine, 151*(4), 264-269.

Paul, J., & Rosado-Serrano, A. (2019). Gradual internationalization vs born-global/international new venture models: A review and research agenda. *International Marketing Review, 36*(6), 830-858.

Sepasgozar, S. M., Hawken, S., Sargolzaei, S., & Foroozanfa, M. (2019). Implementing citizen centric technology in developing smart cities: A model for predicting the acceptance of urban technologies. *Technological Forecasting and Social Change*, *142*, 105-116.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, *36*(1), 157-178.