ENTREPRENEURSHIP AND SUSTAINABILITY ISSUES
ISSN 2345-0282 (online) http://jssidoi.org/jesi/
2023 Volume 11 Number 1 (September)
http://doi.org/10.9770/jesi.2023.11.1(8)

ENTREPRENEURSHIP AND SUSTAINABILITY CENTER
Publisher
http://jssidoi.org/esc/home

INTEGRATED ACCEPTANCE MODEL FOR ON-DEMAND CAR FUNCTIONS: EXPLORING DETERMINANTS OF DRIVERS' ACCEPTANCE

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Received 10 May 2023; accepted 15 August 2023; published 30 September 2023

Abstract. This research paper investigates the factors influencing drivers' acceptance of on-demand car functions (ODCFs) and proposes an integrated acceptance model specific to the ODCFs context. While limited marketing research has explored consumer responses to ODCFs, understanding the determinants of consumers' intention to accept ODCFs is crucial. Existing acceptance models, although effective in explaining variances in consumer behavior, need to be adapted and extended to enhance explanatory power in individual contexts. To address this gap, a comprehensive literature review on ODCFs and related domains was conducted, identifying 74 acceptance factors. Drawing upon the Unified Theory of Acceptance and Use of Technology (UTAUT), the Car Technology Acceptance Model (CTAM), and the identified factors, a multi-level acceptance model tailored to the ODCFs context was developed. At the meso-level, the baseline model incorporates factors such as exposure to ODCFs, domain-specific, symbolic-affective, and moral-normative factors. The micro-level pertains to distinct individual variance components, encompassing socio-demographic attributes, travel behavioral patterns, personality dispositions, and technological inclinations. These micro-level determinants exert a discernible influence on the factors situated at the meso-level of analysis. A partial model that considers cross-level influences and advocates for multi-level research to examine the contextual factors' impacts on acceptance empirically is proposed to operationalize the model. By adopting this approach, researchers can gain deeper insights into the acceptance of ODCFs and shed light on the mechanisms underlying consumer behavior in this specific context.

Keywords: On-demand car functions; acceptance model; UTAUT; CTAM; contextual factors; multi-level research

Reference to this paper should be made as follows: Graesner, T., Vogt, R. 2023. Integrated Acceptance Model for On-demand Car Functions: exploring determinants of drivers' acceptance. *Entrepreneurship and Sustainability Issues*, 11(1), 132-163. http://doi.org/10.9770/jesi.2023.11.1(8)

JEL Classifications: M31, O33, Z13

1. Introduction

Recently, automotive manufacturers like Tesla or Mercedes-Benz have transformed their firms from a product- to a service-centric approach and evolved their vehicles into dynamic service platforms by selling vehicles with built-in add-on features (e.g., adaptive headlights, restricted battery power) that are deliberately restricted by design in their function (Raddats et al., 2019; Garbas et al., 2022; Ng & Wakenshaw, 2017). Similarly, other

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2023 Volume 11 Number 1 (September)
http://doi.org/10.9770/jesi.2023.11.1(8)

manufacturers offer temporary access to features such as heated seats in return for subscription fees (Schaefers et al., 2022). Hence, customers can reconfigure their cars for an additional fee by activating those features throughout their ownership (Garbas et al., 2022). A recent study refers to this phenomenon as "on-demand features". It defines it for the first time as "services that allow customers to temporarily access certain features of a product for an additional fee after the initial purchase has been made" (Schaefers et al., 2022, p. 752). However, in practice, the manufacturers' offering is not restricted to temporary access because the features can be activated permanently, too. This is why this present paper will follow the definition of another study which refers to the same concept as "internal product upgrades" but defines it as "fee-based activation of originally built-in, but deliberately restricted, optional features" (Garbas et al., 2022, n. p.).

ODCFs offer promising benefits for both the customers as well as the manufacturers: Manufacturers generate additional and recurring (in the case of temporary access) revenues by selling ODCFs while holding on to their ownership-centric business model (i.e., selling cars) (Schaefers et al., 2022). Manufacturers are expected to earn an additional 155 billion € in 2022 by offering consumers the opportunity to enhance their vehicles over their lifetime. Moreover, manufacturers can reduce production costs by realizing economies of scale by producing cars with identical features (Garbas et al., 2022).

Customers can unlock and access certain features for a limited time, reacting to a temporary change in their needs because they may not always need it while owning the car (Schaefers et al., 2022). For instance, additional horsepower is an ODCF technically feasible with an electric vehicle. In an environment where speed limits are absent, prioritizing timely traversal and driving gratification, motorists aspire to accelerate beyond their vehicle's existing technical constraints. This underscores a driver's inclination to invest additional horsepower, potentially tethered to the temporal extent remaining within the ongoing expedition (Petry & Moormann, 2020). Consequently, reserving and selectively disengaging systems on an as-needed basis could empower drivers to harness the technological advantages they require precisely when and where they are most opportune (Stiegemeier et al., 2022).

Conversely, ODCFs might elicit unfavorable responses among consumers due to the necessity of incurring charges for expanded functionalities of items they already possess. In a market report, 31% of respondents agreed to the advantages of ODCFs (customizing the car to individual needs); however, at the same time, 35% agreed that it is outrageous to install useful functions in cars without activating them for the customer (Schaefers et al., 2022). The most recent studies found similar results: Wiegand & Imschloss (2021) show that ODCF may induce consumer rejection and feelings of being cheated because consumers perceive pre-installed functions as value included in the price paid, not as options added by the manufacturer (Wiegand & Imschloss, 2021). Schaefers et al. (2022) identified two critical characteristics of ODCFs: tangibility and pricing structure. Regarding tangibility, their results show that while intangible (software-based, e.g. intelligent voice assistant) ODCFs find acceptance, consumers perceive on-demand access to tangible (hardware-based, e.g. seat heating) features as unfair, which explains their reduced purchase intent. Regarding pricing structure, their investigation reveals that fairness perceptions and subsequent behavioral intentions lean more favorably towards ODCFs characterized by flat rate pricing, in contrast to those adopting a pay-per-use pricing framework (Schaefers et al., 2022). In line with these findings, Garbas et al. (2022) show that customer-perceived betrayal drives consumers to respond less favorably to internal (i.e., the feature is already built-in to the product the consumer has purchased, but it is deliberately restricted) vs external (i.e., the feature is physically detached and sold separately from the base product) product upgrades (Garbas et al., 2022).

Little marketing research has examined how consumers respond to ODCFs (Garbas et al., 2022) and consumer reactions to ODCFs have not been examined (Schaefers et al., 2022). Hence, there is a need to understand distinct consumer responses and identify potential variables which might outweigh (e.g., increased flexibility) or increase (e.g., increased complexity) the negative customer perceptions (Garbas et al., 2022). In the same direction, recent

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surveys in related contexts have shown that the consumers' intention to accept or purchase Internet-of-Vehicle (IoV) based services is generally low. Therefore, it is significant to explore the determinants of consumers' intention to accept and purchase IoV-based services (Liang et al., 2020). "A successful real-world deployment of innovative CV applications not only depends on their maturity and usability, but also hinges upon user acceptance” (Li et al., 2021, p. 1). Acceptance is a key factor for the successful introduction and intended use of new technology in the vehicle context. Driver´s acceptance is the precondition for new automotive technologies to achieve their forecasted benefits. A requisite inquiry pertains to assessing drivers' propensity to embrace and engage novel technologies per their intended functionalities (Najm et al., 2006). Nonetheless, the question of how the general acceptance of in-vehicle technology is cultivated lacks a distinct and conclusive answer, as does identifying the most predictive combination of variables across a spectrum of distinct systems (Stiegemeier et al., 2022). Hence, future studies can further explore factors influencing consumers' acceptance of innovations in the automotive context (Chen, 2019). In the context of systems for the driver, acceptance is "the degree to which an individual intends to use a system and, when available, incorporate the system in his/her driving” (Adell, 2010, p. 482). Since there are considerable reservations about ODCFs from the end-user perspective (i.e., unfairness, betrayal), and this innovative technology has yet to be introduced to the market on a mass scale, understanding end-user (i.e., driver's) intentions and attitudes toward ODCFs is crucial if this technological innovation is supposed to be successful. Thus, a thorough comprehension of the constituent elements that shape drivers' inclination toward acceptance bears the potential to drive the success of this technology within the market.

The research objective of this paper is twofold. Firstly, studies in related contexts such as autonomous driving, electric vehicles, driver support systems, and connected vehicles have recognized the need for research into factors that determine drivers' acceptance (Adell, 2010; Adnan et al., 2018; Hanesch et al., 2022; C. Lee et al., 2017; Nordhoff et al., 2018; Osswald et al., 2012; Panagiotopoulos & Dimitrakopoulos, 2018; Seeger & Bick, 2013; Souders & Charness, 2016; Svangren et al., 2017; Xu et al., 2018). However, there is only limited research available on determinants of drivers' acceptance of ODCFs (e.g., Garbas et al., 2022; Ma et al., 2015; Schaefers et al., 2022; Wiegand & Imschloss, 2021), but it is crucial to understand adoption criteria to ensure their usage and thereby create additional value for customers (Juehling et al., 2010). At the same time, the authors call for more research on the interrelation between relevant factors and behavioral outcomes. Hence, there exists a requirement for research aimed at elucidating the intricate interplay between pertinent factors influencing acceptance and corresponding behavioral intentions, leveraging established behavioral models for comprehensive analysis (Nastjuk et al., 2020). The second research objective is connected to behavioral models: Individuals' acceptance and use of information technology have been extensively studied within information systems research. Various theoretical models, drawing from psychological and sociological theories, have been employed to explain the adoption and usage of technology (Venkatesh et al., 2016). Among these, the Unified Theory of Acceptance and Use of Technology (UTAUT), developed through the synthesis of eight technology use models, has emerged as a significant framework to predict behavioral intentions and technology adoption, particularly in organizational contexts (Venkatesh et al., 2003). Nonetheless, a comprehensive examination of factors applicable to consumer technology use contexts is still needed, and recent research has highlighted the importance of context-specific theories to augment the overall understanding and theoretical expansion. Addressing this need, UTAUT2 was devised, enriching UTAUT with additional constructs and relationships tailored to consumer contexts, leading to substantial improvements in explaining variance in behavioral intention (56 percent to 74 percent) and technology use (40 percent to 52 percent) (Venkatesh et al., 2012). The extensive citation count of the original UTAUT and UTAUT2 papers underscores their widespread influence, with thousands of studies conducted in the area (Blut et al., 2022; Venkatesh et al., 2016). Even though established models like the UTAUT2 which has been tailored to the consumer context and proven to explain large portions of the variance in behavioral intention in related contexts such as automated vehicles (Madigan et al., 2017), the literature calls for specific acceptance models related to the individual context: “there is not just one UTAUT specification with a universal set of predictors that applies to all contexts. Instead, the theory’s ability to predict technology use depends on the specific context.” (Blut et al., 2022, p. 53). Other studies formulate that the model needs to be modified and extended to improve the model's explanatory power and specificity (Chen, 2019). Thus, an integrated acceptance model is required in order to include relevant factors in the specific context of ODCFs.

To address the research gaps and overcome the limitations mentioned above, the following sections aim to explore the acceptance of ODCFs by identifying potential factors influencing acceptance from an end-user perspective and developing an integrated acceptance model for the context of ODCFs. The remainder of this paper is structured as follows. Section 2 discusses the current research on the acceptance of ODCFs and related contexts to identify potentially relevant determinants for drivers' acceptance of ODCFs. Section 3 describes the methodology to derive the acceptance model based on the previous literature review. Section 4 introduces the integrated acceptance model and provides the rationale behind its structure. It comprehensively clarifies the model's meso-level construct, which intricately encompasses the primary influences arising from domain-specific instrumental, symbolic-affective, and moral-normative factors. This is complemented by the model's micro-level, which brings together individual variations in acceptance factors. Section 5 presents concluding remarks and highlights potential implications for future research.

2. Literature review & theoretical basis

2.1 Models of technology acceptance

Various prominent models, each characterized by a distinct array of determinants shaping acceptance, have been conceived to elucidate the patterns underlying individuals' embracement and utilization of pioneering technology. For example the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), technology acceptance model (TAM) (Davis, 1989), theory of planned behavior (TPB) (Ajzen, 1991), task-technology fit (TTF) (Goodhue & Thompson, 1995), motivational model (MM) (Davis et al., 1992), unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003, 2012), initial trust model (ITM) (McKnight et al., 2002), diffusion of innovation theory (IDT) (Rogers, 2010), and social cognitive theory (SCT) (Compeau et al., 1999). Numerous investigations have employed these frameworks in their original form or augmented them with novel constructs, resulting in the formulation of models that serve as conduits for their research endeavors across diverse technological contexts (Liang et al., 2020). Nonetheless, within context-specific investigations concerning acceptance, two models frequently assume foundational roles (Lee et al., 2003) and are concisely elucidated in the ensuing discussion. The first model is the TAM, proposed by Davis in 1985, which pertains to the general acceptance of information technology. Within the framework of TAM, the adoption of technology is contingent upon individuals' perception of its Perceived Usefulness (PU) and Perceived Ease of Use (PEoU) (Davis, 1985).

The second model is UTAUT which was introduced by Venkatesh et al. in 2003, consolidating insights from multiple theories, such as the TAM (Davis, 1985), the TPB (Ajzen, 1991), and the MM (Davis et al., 1992). In its original formulation, UTAUT (Venkatesh et al., 2003) posits that technology acceptance is contingent upon several key constructs, including Performance Expectancy, Effort Expectancy, Social Influences, and Facilitating Conditions. Furthermore, the UTAUT model hypothesizes that the influence of these factors is moderated by variables such as gender, age, experience, and voluntariness of use (Venkatesh et al., 2003). Subsequent adaptations of the UTAUT framework, such as UTAUT2, expanded its scope by incorporating three explicitly proposed variables important in the consumer context, i.e., hedonic motivation, price value, and habit (Venkatesh et al., 2012). As a result, the UTAUT has risen as a resilient and impactful framework for investigating factors that underpin the adoption of technology at the individual level. Moreover, its application has been widespread in the realm of comprehending individuals' endorsement of a range of novel information technology innovations (Liang et al., 2020). In a recent research endeavor following the UTAUT framework, scholars have developed a contemporary and refined version of UTAUT, characterized by an expansion beyond the original theory. This augmentation incorporates novel endogenous mechanisms gleaned from disparate theoretical perspectives, such as technology compatibility, user education, personal innovativeness, and technology costs. Furthermore, the study introduces new moderating mechanisms to investigate the applicability of UTAUT across diverse contextual

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2023 Volume 11 Number 1 (September)
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domains, including variations in technology types and national cultural contexts (Blut et al., 2022). Notably, the newly introduced predictors predominantly pertain to users and their circumstances. These findings substantively contribute to the ongoing discourse surrounding the contrast between user-centric technology design and the judicious selection of appropriate users (Blut et al., 2022). ODCFs, as the context of this paper, are also (end-) user-oriented (i.e. the driver). Several studies in related contexts of ODCFs highlight the importance of user-orientation: "results emphasize the importance of user-centered design" (Stiegemeier et al., 2022, p. 79), “distinct consumer responses, which marketers need to understand” (Garbas et al., 2022, n. p.), “to meet customer expectations, the automotive industry will have to change its perspective from product orientation further ("inside-out perspective") to customer orientation ("outside-in perspective")" (Petry & Moormann, 2020, p. 65).

TAM and, specifically, UTAUT can serve as valid starting points to explore drivers' acceptance of ODCFs. Nevertheless, the existing models are not exhaustive in their scope, suggesting the potential for heightened efficacy through additional elucidations and refinements within the framework delineating the pertinent factors that influence technology acceptance within the vehicle context (Stiegemeier et al., 2022). Hence, relevant influencing factors should be identified and extracted from research about specifically ODCFs and related contexts in the next step.

2.2 Influencing factors of technology acceptance towards ODCFs

Many research studies have employed theories of technology adoption to investigate the factors influencing consumers' intention to accept and purchase. Table 1 provides a comprehensive overview of previous studies in related contexts based on a theoretical perspective of technology acceptance. Table 2 summarizes the initial research investigating ODCFs. For example, an antecedent study by Wiegand & Imschloss (2021) explored the fluctuations in consumers' attitudes and purchase intentions concerning the foundational product within the preliminary purchasing phase. The investigation contrasted internal product enhancements marketed as permanent acquisitions through a single upfront payment against those accessible temporarily through rental arrangements (Wiegand & Imschloss, 2021).

In contrast, Schaefers et al. (2022) shifted the focus to the post-purchase phase. They investigated consumers' purchase intentions for non-permanent internal product upgrades, considering the tangibility of the feature (tangible vs intangible) and the pricing structure (monthly subscription vs pay-per-use) (Schaefers et al., 2022). These prior studies offer valuable insights into the context of ODCFs, but they do not provide an acceptance model nor explain the relevant acceptance criteria of ODCFs. As shown in Table 1, previous studies have sought to explain the acceptance of related contexts to ODCFs, such as IoV services, autonomous driving, in-vehicle services, or telematics.

Table 1. Studies on technology acceptance in related contexts of ODCFs

References	Theory	Research context related to ODCFs	Method (data collection and analysis)	Key findings
(Liang et al., 2020)	UTAUT2	Internet of Vehicles Services	Online survey (362 Chinese customers) and PLS-SEM and fcQCA	PE, PV, HA, and TR have significant effects on BI to accept IoV services, and other determinants, e.g., EE, SI, FC, HM, and PR, have no significant effect.
(Nastjuk et al., 2020)	TAM	Autonomous driving	Semi-constructed end-user interviews (20 participants), and online survey (316 participants), and PLS	SN can be a significant factor affecting PU; TR is positively related to UI, PIN predicts PU and PEOU, which in turn, positively affects AT, a significant predictor of UI, RA, and CO positively influence AT and PU, CO positively affects UI

(Nordhoff et al., 2020)	UTAUT2	Conditionally automated (L3) cars	Online questionnaire in eight European countries (9118 participants), confirmatory factor analysis, and structural model consisting of the path relationships (MLE)	HM emerged as the most robust predictor of BI concerning the conditional utilization of automated vehicles. Subsequently, SI and PE exhibited notable predictive power. Age, gender, and familiarity with advanced driver assistance systems yielded statistically significant effects, but with modest magnitudes, below 0.10.
(Garidis et al., 2020)	UTAUT2	Autonomous driving	An online survey in Germany (470 participants) and PLS-SEM	SA has the strongest positive effect followed by HM; DC has the strongest negative effects; Significant positive effects were found for EE, SI, PV, SA, and SDP; PE did not have a significant effect on BI; LDP, EF, and LR also without significant effects
(Walter & Abendroth, 2020)	TAM	Connected vehicular services	The simulator study incl. an online survey (116 participants) and partial least squares (PLS) structural equation modeling	PB enhances a positive AT towards using the connected service; no direct influence of PU on usage adoption; PEOU affects PU but does not affect usage; SN affects UI; Significant positive effect of PRC on PPR and a significant negative effect on TR; TR neither had a significant positive effect on UI, nor a significant negative effect on PPR, an indirect effect of PIC on PR mediated by PRC; PIC lowers PRC, which in turn reduced PPR
(Kim et al., 2016)	TAM	In-vehicle infotainment systems	An online survey in Korea (1070 participants) and PLS	PSE did not have a significant impact on PC and PR but a significant negative impact on PU; TG are important determinant of the perceptions that lead to resistance towards in-vehicle infotainment; SN affects PU, PC, and PR; Relationship between resistance variables (i.e., PU, PC, and PR) and adoption confirmed; PR had the most significant impact on resistance to IVI systems
(Cho et al., 2017)	UTAUT and CTAM	Autonomous vehicles	Driving simulator (68 participants) and PLS	TR caused a significant effect on BI; SA and AX caused a statistically significant effect on BI; AS showed a large number of T statistics, indicating its significant effect on BI; EE caused no statistically significant effect on BI
(Kim et al., 2019)	TAM	On-demand automobile-related services	An online survey in South Korea (318 participants) and multi-group analysis for structural equation modeling	PEOU and PU positively correlated with AT, which in turn positively affected BI; variables for each service are significantly different depending on the characteristics of the service; RA had a significantly positive effect on PU; AC had a positive value for PU and PEOU; PPER not statistically significant in every service; SA significant in medium level service but no significant impact for low- and high-level services
(Leicht et al., 2018)	UTAUT	Autonomous car	Online survey in France (241 participants) and Sem and multi-group analysis	PE, EE, and SI are positively related to the PI of autonomous cars; CI introduces a moderating impact on the connections linking various precursors to the adoption of autonomous vehicles, and PI attributed to these vehicles; This moderation notably gains greater prominence when CI is at elevated levels as opposed to instances where CI registers lower values
(Chen, 2019)	TAM-TTF	Telematics	A survey in Taiwan (400 participants) and PLS	PU and PEOU affect adoption intention; The impact of technology characteristics exhibited a more pronounced influence on TTF compared to the effects attributed to task characteristics; individual perceptions about EN and UQ also exert substantial effects on PU and PEOU; A performance gap negatively affects PEOU; PIN has a positive impact on PEOU, particularly for those with shorter driving experience; PU influences adoption intentions, but its impact may be hindered by driving experience

ISSN 2345-0282 (online) http://jssidoi.org/jesi/
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http://doi.org/10.9770/jesi.2023.11.1(8)

(Adell, 2010)	UTAUT	Driver support systems	Pilot test (20 inhabitants) and linear regression analysis	The importance of SI for BI was highlighted, but no significance of EE; traffic safety related to all constructs due to fundamental importance for driver, passengers, and authority
(Razak et al., 2022)	TAM	In-vehicle applications	308 responses among Malaysians and linear and non-linear regression analysis	factors such as knowledge about in-vehicle applications can significantly affect TR and SI, AT and UI; an informed choice becomes attainable for the user when they possess a comprehensive awareness of both the benefits and constraints inherent to the applications in question; gender and driving experience have a moderating effect on the BI; Neither age nor gender wield a substantial impact on user acceptance, as indicated by the absence of significant effects; the frequency of weekly driving or accumulated driving experience fails to exert a noticeable influence on user acceptance levels; TR, SC, and SI may also influence the PU and PEOU, which in turn positively affects AT toward using an in-vehicle application, a significant predictor of UI
(Yoon & Cho, 2016)	TAM	Smart car service	Web survey in South Korea (427 respondents) and structural equation model (SEM)	CO of user experience with existing technologies is a critical factor affecting consumer evaluations of a convergence service; TTF is a significant positive factor mediating the effect of PU and EN on adoption intention; Visual design positively influences user's perception and adoption intention
(Yu & Cai, 2022)	TPB and TRA	Intelligent connected vehicles	An online survey in China (500 respondents) and SEM	PSR and PPR have negative effects on TR; the data breach anxiety positively influences PPR; TR can directly affect AT and BI; BI is influenced by the factors of PSR, PPR, trust, and AT
(Vafaei-Zadeh et al., 2021)	C-TAM-TPB and UTAUT2	Car Dashcam	Structured digital questionnaires (232 respondents) and PLS	No relationship between PI and PU was found, in contrast to a significant relationship between the former and PEOU; perceived uniqueness was found significant to both PU and PEOU; both PU and PEOU were identified as factors influencing AT; PU did not affect intention; PBC, SI, AT, and TR significantly affected the BI to use the dashcam
(Park et al., 2013)	UTAUT	Smartphone-car connectivity	Online survey (1070 respondents) and PLS	FC and TG positively affect BI to use car connectivity functionality; mobile literacy and PSE have no significant relationship
(Noraga et al., 2021)	UTAUT2	On-demand services application	296 respondents and SEM	PE, EE, HA, and immediacy positively influenced the intention to use on-demand services applications; HA negatively moderated the intention to use on-demand services applications
(Chan & Lee, 2021)	TAM and UTAUT	5G Connected Autonomous Vehicle	An online questionnaire (211 participants in Malaysia) and PLS-SEM	CO and PIN were found to have a positive influence on BI; TR exhibits a strong direct effect on BI; PU, PEOU, and SI were found to have no relationship with BI, but relationships partially mediated by TR
(Yeap et al., 2017)	UTAUT2 and DOI	On-Demand Services (e.g. UBER)	Survey (330 respondents) and PLS	SI, Personalization, and PR with substantial influence on adoption decisions; adoption intentions will strongly result in intentions to recommend the technology to others; immediacy, EE, FC, HM, PV, and PE were found to have no impact on ODS adoption
(Panagiotopoulos & Dimitrakopoulos, 2018)	TAM	Autonomous driving	Web-based questionnaire (483 respondents) and Pearson product-moment inter-correlations and multiple regression analyses (MRAs)	PU, PEOU, TR, and SI impact on intention to use Avs; TR also had a positive impact on BI; SI also had a positive impact on BI; SI and TR constructs have a negative interaction; PEOU seems to have the more minor influence on the attitudes of consumers towards the use of AVs

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2023 Volume 11 Number 1 (September)
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(Abd Aziz, 2016)	CTAM	New Car Technologies	Questionnaire and PLS	Brand service quality has a strong direct positive effect on brand loyalty; technology anxiety moderates the relationship between brand service quality, brand value, and brand loyalty
(Hanesch et al., 2022)	UTAUT	Connected car services	Survey (260 respondents) and PLS-SEM	Age, gender, and technical affinity show moderating effect just for one relation significantly; Risk tolerance has emerged as a prevalent moderator, demonstrating its potential as a promising criterion for gauging usage intentions concerning connected car services; risk tolerance indicated a dampening effect on the relation of SI on BI; risk tolerance for activities on the Internet seemed to strengthen the relation of PE and BI; Experience also indicated an influencing effect strengthen the positive relation of SI and BI
(Osswald et al., 2012)	UTAUT (CTAM)	Information technology in the car	Questionnaire (21 subjects) and internal reliabilities (Cronbach's α)	The proposed scales exhibit strong internal consistency, and the outcomes suggest that participants demonstrate an awareness of the influences related to safety and anxiety when engaging with information technology during driving scenarios; low values for FC
(Nordhoff et al., 2019)	UTAUT3 + CTAM	Automated vehicle	Literature review (124 records)	28 acceptance factors that represent seven main acceptance classes; 6% exposure of individuals; 22% domain-specific; 4% symbolic-affective factors; 12% moral-normative factors 28% socio-demographic profile; 15% travel behavior; 14% personality
(Stiegemeier et al., 2022)	TAM (integrated model)	in-vehicle technology	Online survey (304 participants) and descriptive statistics, bivariate correlations, independent samples t-Tests, content analysis	Through an inductive content analysis, a total of thirteen distinct categories emerged; Need, Context and Task, and Reliability were found to be associated with PU; Increased Effort and Aversion emerged as categories closely linked to PEOU; In addition, the influencing factors are further extended with the Preference for Own Action, Distrust/Trust, Safety, Knowledge, and Habit
(Yu & Jin, 2021)	TAM (adapted)	Intelligent Connected Vehicle Infotainment in the 5G-V2X	Questionnaire survey (502 respondents) and PLS-SEM	PU, PEOU, CI, and SI directly exert influence on AT and UI, contributing to 46.8% and 73.4% of the observed variance, respectively; PR has an insignificant path with attitude and intention; driving experience moderation effect exists between PR and usage intention
(Hampton-Sosa, 2019)	TAM	Music Streaming (access-based service)	Online survey (139 cases) and PLS-SEM	PEOU is positively related to PU and EN; Both PU and EN exhibit positive associations to purchase; PU and EN are positively influenced by perceived product format usefulness; PU is positively related to PI and negatively related to unauthorized downloading intention; EN is positively related to PI; Perceived ease of product modification, perceived ease of product trial, and perceived ease of product sharing are ultimately positively related to adoption and negatively related to the intention to engage in digital piracy
Note: Accessibility (AC); Affective satisfaction (AS); Attitude (AT); Anxiety (AX); Behavioral intention (BI); Consumer innovativeness (CI); Compatibility (CO); Desire for control (DC); Effort expectancy (EE); Environmental friendliness (EF); Perceived enjoyment (EN); Facilitating conditions (FC); Habit (HA); Hedonic motivation (HM); Loss of driving pleasure (LDP); Legal regulations (LR); Perceived benefit (PB); Perceived behavioral control (PBC); Privacy concerns (PRC); Perceived complexity (PC); Performance expectancy (PE); Perceived ease of use (PEOU); Personal innovativeness (PIN); Purchase intention (PI); Perceived information control (PIC); Perceived performance risk (PPER); Perceived privacy risk (PPR); Perceived risk (PR); Prior similar experience (PSE); Perceived security risk (PSR); Perceived usefulness (PU); Price value (PV); Relative advantage (RA); (Perceived) safety (SA); System characteristics (SC); Security & data privacy (SDP); Social influence (SI); Subjective norm (SN); Technographics (TG); (Initial) trust (TR); Task-technology-fit (TTF); Usage intention (UI); Perceived Uniqueness (UQ)				

Source: Own elaboration

ENTREPRENEURSHIP AND SUSTAINABILITY ISSUES
ISSN 2345-0282 (online) http://jssidoi.org/jesi/
2023 Volume 11 Number 1 (September)
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Table 2. Illustrative review of research on ODCFs

References	ODCFs	Key purpose	Key findings
(Ma et al., 2015)	Autopilot technology, adaptive cruise control system)	empirically analyze the influence of innovation locus and innovation newness on the adoption of the complete product, consisting of both the base product and an additional feature	The introduction of innovative features as external components, as opposed to internal components, positively impacts product adoption intentions for the entire product (base product + added feature), with the influence of innovation locus being significant specifically for highly novel innovations rather than incrementally new ones
(Petry & Moormann, 2020)	On-demand horsepower	demonstrate promising avenues for the design of payment-enabled services within the domain of connected cars, leveraging the process thinking approach as its foundation	The sequential actions required to fulfill a driver's solicitation for on-demand horsepower during a specific timeframe, coupled with the facilitation of mobile payment for this service
(Schaefers et al., 2022)	Seat heater, intelligent voice assistant	empirically examine the effects of feature tangibility and feature pricing on consumers' intentions to purchase non-permanent internal product upgrades	Reveal a decreased propensity to purchase tangible features compared to intangible ones, while also reveal higher purchase intentions for flat-rate pricing compared to pay-per-use pricing
(Wiegand & Imschloss, 2021)	Different features, e.g., extended range, improved acceleration	examine: (a) the variations in consumers' evaluations of the base product between continuous Over-The-Air (OTA) software updates and external hardware upgrades, and (b) the impact of feature pricing on consumer reactions toward OTA software updates in contrast to internal product upgrades	Compared to conventional standard products, the inclusion of products with an ongoing upgradability feature exerts a positive influence on consumers' assessments of the fundamental product. Nonetheless, evaluations of products offering continuous OTA software updates tend to be slightly less favorable when contrasted with those presenting external hardware upgrades; temporary OTA software updates are subject to relatively less favorable consumer evaluations in comparison to their permanent counterparts, while no statistically significant variances are evident for internal product upgrades
(Garbas et al., 2022)	Digital radio, rear-view camera, driving performance software, head-up display	examine the effects of internal product upgrades, as opposed to external ones, on consumers' responses, specifically investigating their willingness to pay for the feature and their loyalty intentions towards the firm	(1) presents novel evidence indicating that consumers' behavioral intentions exhibit less favorability towards internal product upgrades compared to external ones, (2) unveils the sequential mediating effects of perceived feature ownership and perceived betrayal, elucidating the underlying mechanisms through which these effects occur, and (3) identifies three important moderating factors - upgrading responsibility, feature tangibility, and product-identity-relevance - that enable firms to mitigate the negative consequences associated with internal product upgrades

Source: Own elaboration

From a theoretical perspective, a substantial portion of the research endeavors strives to examine the underpinnings of acceptance through the lens of singular theories, such as TAM (Davis, 1989), TPB (Ajzen, 1991), or UTAUT (Venkatesh et al., 2003, 2012). Concomitantly, these studies often employ the foundational TAM or UTAUT as a conceptual foundation, incorporating or omitting variables from the original models and relevant research, driven by theoretical and practical motivations (Stiegemeier et al., 2022). The review underlines that research approaching the prediction of technology acceptance of ODCFs is fragmented and inconclusive. The determinants influencing the acceptance of ODCFs and the specific factors that hold significant importance in this context remain uncertain and require further investigation. To provide a comprehensive understanding of the adoption decision-making of ODCFs, scholars have advocated for the integration of diverse theories or the incorporation of supplementary factors contingent upon specific contextual nuances, intending to augment the model's capacity for explanatory efficacy (Chen, 2019; Herrenkind et al., 2019). The primary objective of the presented study is to furnish a comprehensive integrated model encompassing the factors that influence drivers' acceptance of ODCFs. Derived from an extensive literature review, the research question can be formulated as

ISSN 2345-0282 (online) http://jssidoi.org/jesi/
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follows: *What are the critical determinants in the driver's acceptance of on-demand car functions, and how can they be integrated into a comprehensive acceptance model to better understand consumer behavior in this context?*

Therefore, in the next step relevant theories and constructs that have been verified in the different contexts are integrated, aiming for the highest explanatory power of the model.

3. Methodology

Following Kaur and Rampersad (2018), factors identified by existing and suitable acceptance models are synthesized in conjunction with factors derived from the literature review on technology acceptance in related contexts and studies on ODCFs (Kaur & Rampersad, 2018; Nordhoff et al., 2019). Therefore, the methodology of the present paper is structured in four components (see Figure 1).

First, the underlying theories and assumptions that provide the basis for the model are introduced. Second, for the composition of the model, the guidelines for developing a multi-level framework of technology acceptance and use (Venkatesh et al., 2016) were considered. Third, to identify relevant determinants for the context of ODCFs, a literature review was conducted by the guidance on conducting a systematic literature review (Xiao & Watson, 2019). In adherence to the approach described by Nordhoff et al. (2019) and Zhang et al. (2019), no specific protocol was generated or registered for this review (Nordhoff et al., 2019; Zhang et al., 2019).

A comprehensive review of relevant peer-reviewed articles listed in Scopus and Web of Science databases was conducted to construct a theoretical model for predicting driver's acceptance of ODCF, and to explore the factors influencing ODCF acceptance. The review encompassed articles available until May 2023 that applied the acceptance models of UTAUT or TAM. Since there is no available research on the driver's acceptance of ODCFs, the search was extended to related contexts of ODCFs. Hence, the selection of articles included those whose titles, abstracts, or keywords featured the research query of the following keywords: On-demand car functions, On-demand automobile-related service(s), Information technology in the car, New Car Technologies, Connected car service(s), Smartphone-car connectivity, Driver support system(s), Telematic(s), In-vehicle infotainment system(s), Connected vehicle(s), Internet of Vehicles Service(s), Access-based service(s), Autonomous driving, Automated vehicle(s), acceptance, driver, TAM, UTAUT.

Further inquiries were conducted via Google Scholar to expand the available range of eligible studies for sample selection. To maintain uniformity, identical keywords were utilized. The reference lists of all studies that satisfied the established search criteria were systematically examined to identify additional pertinent studies.

In the initial phase, 1850 full-text records were retrieved, which were subsequently subjected to a thorough assessment of eligibility. Among them, duplicate records were identified and removed, and records were excluded due to their deviation from our predefined search criteria. These excluded records focused on alternative technologies such as insurance, automated shuttles, trucks, wearables, and buses. Furthermore, review-based studies, which had already discussed the outcomes of some of the studies satisfying our eligibility criteria, were omitted. Consequently, 27 records were retained for the qualitative analysis in the final phase (see Table 1).

Following the methodology outlined in Nordhoff et al.'s (2019) study, an analysis was conducted to determine the number of studies that examined specific factors related to acceptance of the respective context (Nordhoff et al., 2019). Hereby, the focus was on the acceptance determinants incorporated in the models of the studies and their relative importance. The statistical results have been extracted from the studies resulting in an overview of over 300 relationships between variables, including the effects and significance level. Based on that, the determinants that revealed significant statistical results were extracted again. The identical ones were grouped within these

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http://doi.org/10.9770/jesi.2023.11.1(8)

relevant determinants, and the number of studies they occurred was counted. In addition, factors that are named differently in the different acceptance models but have the same meaning were grouped. Then, the identified determinants were checked against the existing acceptance models to identify the overlap and additional factors. Out of the remaining additional factors, group classes were formed.

Fourth, in addition to the determinants identified from technology acceptance studies in contexts relevant to ODCFs (see Table 1), the results and factors from the few existing studies on the actual topic of ODCFs (see Table 2) were also incorporated into the development of the integrated acceptance model.

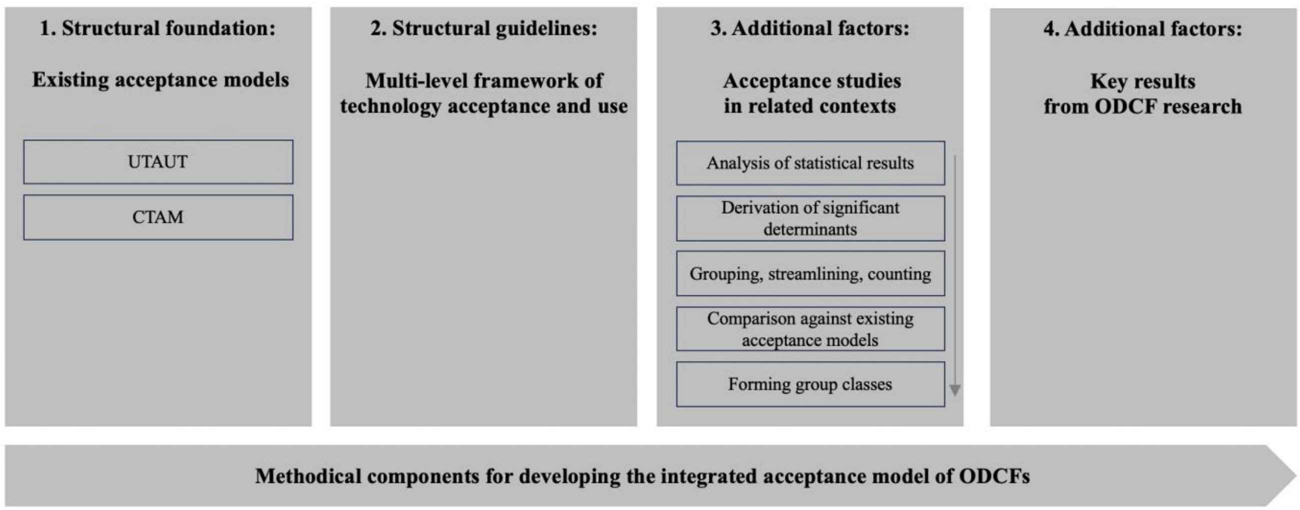

Figure 1. Structured methodology including four components
Source: Own elaboration

4. Theoretical model

4.1 Existing acceptance models as structural foundation

The first theoretical framework that provides the structural foundation for the ODCFs acceptance model is the state-of-the-art and revised UTAUT model proposed by Blut et al. in 2022. Their devised model extends the existing theory by incorporating four supplementary predictors that have demonstrated a more substantial impact on numerous technologies compared to certain original predictors of the theory and predictors within the UTAUT2 framework: “The results suggest that four new predictor variables […] explain substantial variance in intention and use above and beyond the variance explained by current predictors” (Blut et al., 2022, p. 51).

The four additional predictors in their model are technology compatibility, user education, personal innovativeness, and technology costs. Regarding technology compatibility, the authors underscore the notion that the assimilation of a novel radical technological innovation can present formidable hurdles for an organization (Hill & Rothaermel, 2003), particularly when the new technology is integrated into an established platform or ecosystem (Blut et al., 2022). ODCFs represent a technological innovation part of an existing platform (i.e., the connected car). Hence, this predictor could be specifically relevant to the present context of this paper. Next, user education and personal innovativeness emerged as pivotal user attributes with considerable influence over adoption determinations. Lastly, the study highlighted the salient significance of the monetary costs associated with procuring or utilizing the technology for the user (Blut et al., 2022). Also, the studies in the ODCFs context find that pricing structure is a key characteristic, and different results were found regarding the purchase intention depending on the ODCFs tangibility (Schaefers et al., 2022).

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Furthermore, the results of their meta-analysis revealed variance in relationships, which suggests the presence of moderating variables exerting an influence. Hence, the authors conclude that the theory's ability to predict technology use depends on the specific context and suggest always considering moderators when applying UTAUT (Blut et al., 2022). With technology types and national culture, their results revealed important moderators. Specifically, technology types can be utilized to compose a UTAUT specification that predicts technology use in different contexts (Blut et al., 2022). Previous studies of ODCFs and related contexts found significant differences within ODCFs related to the technology type. For instance, the feature tangibility (i.e., the feature composition between hardware and software) was identified as a key characteristic for ODCFs (Schaefers et al., 2022), and negative customer perceptions are attenuated when consumers upgrade an intangible (vs. tangible) feature (Garbas et al., 2022).

Taken together, the revised UTAUT model provides a state-of-the-art basis for developing the ODCFs acceptance model. Specifically, the additional predictors and moderators should be considered. However, the need to adapt the model for specific contexts is emphasized: "UTAUT should be extended by considering additional contextual differences that characterize the specific context in which the theory is employed" (Blut et al., 2022, p. 51).

The second theoretical underpinning is the CTAM, introduced by Osswald et al. in 2012, which serves as a predictive framework for accepting in-car technology. CTAM postulates a linkage between in-car technology acceptance and constructs derived from the UTAUT – encompassing performance expectancy, effort expectancy, social influence, and facilitating conditions. Moreover, CTAM incorporates additional factors such as perceived safety and anxiety, potentially influencing information systems' acceptance within vehicular environments (Osswald et al., 2012). The CTAM was utilized in studies related to autonomous vehicles (Cho et al., 2017), new car technologies (Abd Aziz, 2016), and automated vehicles (Nordhoff et al., 2019). CTAM expands the scope of the UTAUT model, facilitating an explanation and projection of drivers' acceptance of information technology within the vehicular context. This extension entails including supplementary variables that align with the characteristics of in-car technology, rendering them amenable for integration within the acceptance framework of ODCFs. However, the authors also mention: "We cannot exclude that there will be further determinants that need to be considered within the car context" (Osswald et al., 2012, p. 57); hence additional potentially relevant determinants of ODCF acceptance must be included.

4.2 Multi-level framework of technology acceptance and use providing structural guidelines

Arising from a meticulous evaluation of research endeavors that have employed, extended, or amalgamated the preceding UTAUT models, Venkatesh et al. (2016) propose a multi-level framework that can serve as the theoretical foundation for research. The framework distinguishes between individual-level contextual factors, higher-level contextual factors, and a baseline model formed by the main effects of the previous UTAUT2 model (Venkatesh et al., 2016). The strength of the framework is its holistic and comprehensive overview of the possible factors impacting technology acceptance in a specific context (Nordhoff et al., 2019), which corresponds with the objective of this paper to develop an integrated context-specific acceptance model.

Regarding the baseline model, the authors posit that the primary effects of UTAUT/UTAUT2 ought to establish the baseline model, a decision driven by the principle of parsimony. This approach aims to enhance the precision of existing contextual impacts and identify potential novel contextual effects within the framework (Venkatesh et al., 2016). However, the present paper will follow the proposal of Blut et al. (2022) and include the predictors of the revised and state-of-the-art UTAUT model as the baseline model since, on the one hand, it represents the most actual research and, on the other hand, supports the objective for an extension by considering additional contextual differences that characterize the specific context in which the theory is employed (Blut et al., 2022). Nevertheless, the baseline model suggests individual beliefs, including performance expectancy, effort expectancy, social influence, hedonic motivation, and price value (Venkatesh et al., 2016). According to the authors' proposition, there are potentially relevant determinants for ODCFs at two levels. First, the meso-level

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encapsulates the fundamental influences from the instrumental domain-specific, symbolic-affective, and moral-normative dimensions inherent to ODCFs. In line with the proposition of Nordhoff et al. (2016), interconnections among the factors constituting the domain-specific, symbolic-affective, and moral-normative facets of the model are postulated (Nordhoff et al., 2016). Second, the micro-level encompasses individual variability factors. These include user attributes which can be expanded by including other demographic variables, as well as technology attributes, task attributes, rationale attributes, and events/time. These contextual factors engender different extensions to the baseline model (Venkatesh et al., 2016).

4.3 Acceptance studies in related contexts

The literature review about technology acceptance in related contexts of ODCFs (see Table 1) revealed that significant relationships have been identified in the respective studies. During the critical literature review across contexts related to OCDFs, 74 individual acceptance factors were identified (see Table 3). Each factor significantly affected the respective outcome or other variables in the studies' models.

However, the variables are not free from overlap since they are utilized in different acceptance frameworks with different names but the same meaning. For instance, during the formulation of the original UTAUT model, the authors acknowledge the similarity between performance expectancy and perceived usefulness, as well as between effort expectancy and perceived ease of use (Venkatesh et al., 2003). Hence, as a preliminary action, equivalent factors are condensed as follows: Performance expectancy corresponds to perceived usefulness, effort expectancy aligns with perceived ease of use, facilitating conditions equate to perceived behavioral control, and social influence corresponds to the subjective norm. The remaining number of factors is 70. Out of that, the acceptance factors exhibiting a significant effect in many studies (n = five or more) are as follow: Performance expectancy/Perceived usefulness, Effort expectancy/Perceived ease of use, Social influence, Hedonic motivation, Compatibility, Innovativeness, Perceived safety, and Trust.

Moreover, 47 acceptance factors were identified through only one analyzed study, which speaks for a broad variety of relevant acceptance factors and a high level of granularity. At the same time, it underlines the need for an integrated or extended acceptance model since the base models (e.g., TAM, UTAUT) does not incorporate enough relevant determinants for the context of ODCFs. This finding is in line with Blut et al. (2022): "There is not just one UTAUT specification with a universal set of predictors that applies to all contexts. Instead, the theory's ability to predict technology use depends on the specific context" (Blut et al., 2022, p. 53).

Table 3. Overview of ODCFs factors and the number (n) of studies that found the factors to be significant

Factor number	Level	Factor class	Acceptance factor	n
1.	Meso	Baseline model	Facilitating conditions	4
2.			Performance expectancy	8
3.			Effort expectancy	6
4.			Social influence	13
5.			Hedonic motivation	5
6.			Price value	3
7.			Habit	3
8.			Compatibility	5
9.			Education	1
10.			(Personal) Innovativeness	7
11.			Costs	1
12.			Anxiety	3
13.			Safety	5
14.		Exposure to ODCFs	Experience / Prior similar experience	3
15.			Knowledge	2
16.		Domain-specific system evaluation	Perceived betrayal	1
17.			Perceived feature ownership	1
18.			Perceived usefulness	12

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19.			Perceived ease of use	9
20.			Relative advantage	2
21.			Security	1
22.			Service and vehicle characteristics / System characteristics	2
23.			Task-technology fit	2
24.			Perceived complexity	1
25.			Accessibility	1
26.			Perceived ease of product modification	1
27.			Perceived ease of product trial	1
28.			Perceived uniqueness	1
29.			Visual attractiveness	1
30.			Immediacy	1
31.			Fairness perception	1
32.		Symbolic-affective system evaluation	Subjective norm	2
33.			(Perceived) Enjoyment	3
34.		Moral-normative system evaluation	Product-identity relevance	1
35.			Expected upgrade effort	1
36.			Expected product quality	1
37.			Perceived risk	4
38.			Data privacy	1
39.			Perceived benefits	1
40.			Privacy concerns	1
41.			(Perceived) Privacy risk	2
42.			Perceived information control	1
43.			Data breach anxiety	1
44.			Perceived security risk	1
45.			Perceived performance risk	1
46.			Perceived privacy	1
47.	Micro	Socio-demographics	Age	1
48.			Gender	2
49.			Household structure	1
50.			Income	1
51.			Employment	1
52.			Residential situation	1
53.			Driving license	1
54.			Locality	1
55.			Self-reporting capabilities	1
56.		Travel behavior	Access to mobility	1
57.			Travel purpose	1
58.			Attitude toward using travel modes	1
59.			Frequency of travel mode use	1
60.			Medical condition	1
61.			Accidents/accident involvement	2
62.			Driving mileage	1
63.		Personality	Trust/Distrust	9
64.			Desire for control	1
65.			Preference for own action	1
66.			Resistance	1
67.			Technographics	2
68.			Personalization	1
69.			Risk tolerance (on the Internet)	1
70.			Perceived behavioral control	1
71.		Technology	Feature tangibility	2
72.			Pricing structure	1
73.			Type of feature	1
74.			Technology type (mobile, online, transaction)	1

Source: Own elaboration

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Comparing the identified acceptance factors to the established models, it can be seen that all factors and moderators from the UTAUT2 model (i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, age, gender, experience).

In comparison to the most recent UTAUT model, which extends the original theory with new endogenous mechanisms (i.e., technology compatibility, user education, personal innovativeness, and costs of technology) and new moderating mechanisms (e.g., technology type and national culture) (Blut et al., 2022), all the additional endogenous mechanisms have been identified by the literature analysis, too. This signalizes, that the current state-of-the-art research is represented, and a high level of explanatory power can be expected. Considering these findings and confirming what has been mentioned before (see Chapter 4.2), the revised UTAUT model should be considered in the structural foundation for the integrated acceptance model for ODCFs, which the authors also suggest: "when employing UTAUT in future technology studies, researchers should consider the revised UTAUT that includes these four new predictors" (Blut et al., 2022, p. 51).

Regarding CTAM, in the original study, two factors have been identified as relevant (i.e., perceived safety and anxiety) (Osswald, Kun, et al., 2012); both factors have also been found significant by other studies from the literature review.

In total, 13 factors have been derived from the revised UTAUT model (performance expectancy, effort expectancy, social influence, price value, hedonic motivation, facilitating conditions, habit, compatibility, education, personal innovativeness, costs) and CTAM model (Safety, Anxiety) are integrated into the baseline model on meso-level.

Moreover, the study by Blut et al. (2022) found substantial variation in effect size that moderators and several interaction effects between technology types can explain.

Their minimum expectation is that studies include individual characteristics as moderators (i.e., age and gender) but also integrate technology types as moderators (Blut et al., 2022). To follow this suggestion, age & gender are included as moderators in socio-demographics on the micro-level. In addition, technology types (mobile technology, online technology, and transaction technology) are moderators in the micro-level technology class.

Lastly, the 58 factors next to the baseline model are consolidated into eight-factor classes, whereby acceptance classes 1-4 are located at the meso-level, while Classes 5-8 are located at the micro-level (Nordhoff et al., 2019):

- Class 1 (Factor 14, 15): Exposure to ODCFs
- Class 2 (Factors 16–31): Domain-specific system evaluation
- Class 3 (Factors 32–33): Symbolic-affective system evaluation
- Class 4 (Factors 34–46): Moral-normative system evaluation
- Class 5 (Factors 47–55): Socio-demographics
- Class 6 (Factors 56–62): Travel behavior
- Class 7 (Factors 63–70): Personality
- Class 8 (Factors 71-74): Technology

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4.4 Key results from ODCF research

Besides the factors identified from the existing acceptance theories and the acceptance studies in related contexts of ODCFs, additional factors were extracted from the existing literature in the context of ODCFs (see Table 2). As outlined before and mentioned by the authors of the respective studies, the research on ODCFs is limited; for instance, Schaefers et al. (2022) mention "neither have ODCFs been conceptually delineated and defined, nor have consumer reactions to such services been examined" (Schaefers et al., 2022, p. 752). In contrast to existing empirical research in the marketing domain on hardware upgrades (Ülkü et al., 2012), software upgrades, such as in the case of ODCFs "have not been examined thus far" (Wiegand & Imschloss, 2021, p. 2). In distinction to related phenomena such as external product upgrades through add-on features, product versioning, product upgrading, and over-the-air updates, "little marketing research has examined how consumers respond to having to pay for activating deliberately restricted features in a physical product" (Garbas et al., 2022, n. p.).

Schaefers et al. (2022) underscore that consumers' fairness perceptions - defined as judgments of outcome/process reasonability (Xia et al., 2004) - impact purchase decisions. Unfairness perceptions reduce purchase intentions and increase complaints, mistrust, and switching behaviors (Cziehso et al., 2019; Namkung & Jang, 2009; Nguyen & others, 2013; Blodgett et al., 1997). In exploring ODCFs, the authors focus on tangibility and pricing. Tangibility involves software-based intangibles vs. hardware-based tangibles. Consumer reactions vary; software features (e.g., intelligent voice assistant) are accepted more, whereas hardware features (e.g., seat heating) are approached with caution, affecting purchase intentions (Atasoy & Morewedge, 2018; Schaefers et al., 2022). In pricing, flat rates (similar to Netflix or Spotify) are preferred and viewed as fairer than pay-per-use due to simplicity. Participants showed higher purchase intent for flat rates, emphasizing its role in ODCF acceptance (Schaefers et al., 2022). Lastly, while tangibility and pricing are vital, ODCFs' design should consider core (e.g., car driving assistance) vs peripheral features (e.g., phone integration), prompting future research on diverse ODCF types, such as safety vs entertainment (Schaefers et al., 2022).

Garbas et al. (2022) investigated consumer reactions to internal versus external product upgrades, emphasizing normative expectations and psychological ownership. They theorized adverse reactions to internal upgrades, viewed as trust breaches when charging for perceived inherent features. Comparably, Wiegand & Imschloss (2021) distinguished between software and hardware upgrades, assessing consumer valuation differences.

Garbas et al. (2022) highlighted behavioral repercussions from internal product upgrades, notably increased perceived feature ownership leading to feelings of betrayal and negative consumer responses. Strategies suggested for these effects' mitigation involved three factors: upgrading responsibility, feature tangibility, and product-identity-relevance. Internal upgrades for intangible features (e.g., driving performance software), received less backlash, arguably due to weaker feature ownership feelings than tangible features (e.g., rear-view cameras). The tangible upgrades intensified feelings of betrayal, whereas external upgrades were less contentious (Garbas et al., 2022). This research adds dimension to Schaefers et al. (2022), emphasizing monthly internal product upgrade subscriptions.

Garbas et al. (2022) pinpointed mediators and moderators influencing ODCF end-user acceptance: perceived betrayal, a mediator, signifying a firm's intentional norm violation in consumer relations (Grégoire & Fisher, 2008), affects behavioral intentions like purchase and loyalty. Another mediator, perceived feature ownership, suggesting personal attachment to an object or part thereof (Pierce et al., 2003), creates feelings of betrayal from internal upgrades, diminishing consumer sentiments. As for moderators, feature tangibility (the balance between tangible and intangible feature elements) impacts consumer reactions based on upgrade type. Lastly, product-identity-relevance, i.e., how a product reflects a user's identity (Kwon et al., 2017), moderates reactions: individuals with high product-identity relevance respond negatively to tangible versus intangible upgrades, a response mellowed in those with lower product identity relevance (Garbas et al., 2022).

Wiegand & Imschloss (2021) executed four studies with relevant findings in each.

Firstly, upgradeability increases vehicle value, with hardware upgradeability preferred over software, improving consumer evaluations regarding attitude and purchase intention.

Secondly, consumers differentiate software and hardware upgrades, each having distinct value across product qualities. Superior hardware quality does not enhance perceived software upgrade effectiveness.

Thirdly, they probed mechanisms linking software vs hardware upgradeability to consumer attitudes, finding mediation via expected product quality and upgrade effort. Bundling software upgrades increased perceived product quality.

Fourthly, they explored modular software upgrades, focusing on unlocking pre-installed functions and continuous innovation. Upgrades based on a subscription model, like temporary functionality access, were discussed. Unlocking product features could be perceived as unfair, mirroring insights from Garbas et al. (2022) and Schaefers et al. (2022). The utility of withheld functions versus continuous innovation merits further study, as withholding might devalue consumer evaluations (Wiegand & Imschloss, 2021).

Taking the results together, two mediating determinants can be identified for the context of ODCFs: First, expected upgrade effort describes the consumer input, such as time and decision-making, required for upgrade implementation. Minimizing perceived effort by underscoring ease of integration could benefit firms. Second, expected product quality relates to the upgrade's enhancement of product performance and durability. Their results show that consumers perceive software upgrades as indicative of diminished product quality relative to hardware upgrades. This finding resonates with earlier studies emphasizing a consumer inclination towards tangible products, attributing them with superior characteristics (Atasoy & Morewedge, 2018; Peck & Shu, 2009). Moreover, the mediation through product quality significantly outweighs upgrade efforts (Wiegand & Imschloss, 2021). This supports Christensen's (2011) assertion that performance metrics take precedence over usability facets in the context of product innovation adoption (Christensen, 2011).

From the results of studies related to the specific context of ODCFs, in total, nine factors have been identified, i.e. fairness perception (Schaefers et al., 2022), feature tangibility (Garbas et al., 2022; Schaefers et al., 2022), pricing structure (Schaefers et al., 2022), types of features (Schaefers et al., 2022), perceived betrayal (Garbas et al., 2022), perceived feature ownership (Garbas et al., 2022), product-identity-relevance (Garbas), expected upgrade effort (Wiegand & Imschloss, 2021), and expected product quality (Wiegand & Imschloss, 2021).

4.5 Integrated acceptance model of ODCFs

The acceptance model for ODCFs has been developed by building on two already established acceptance models (i.e., the state-of-the-art UTAUT and CTAM) and following the structural guidelines of a multi-level framework whereby relevant factors derived from both acceptance research in related contexts and studies in the actual context of ODCFs, have been integrated as factor classes on meso- and micro-level (see Figure 2). In accordance with the methodology advocated by Nordhoff et al. (2019), the individual variance factors situated at the micro-level exert both direct and indirect influences on the factors at the meso-level, often mediated or moderated by intervening mechanisms. Furthermore, the model posits interconnections among the components comprising the domain-specific, symbolic-affective, and moral-normative facets (Nordhoff et al., 2019).

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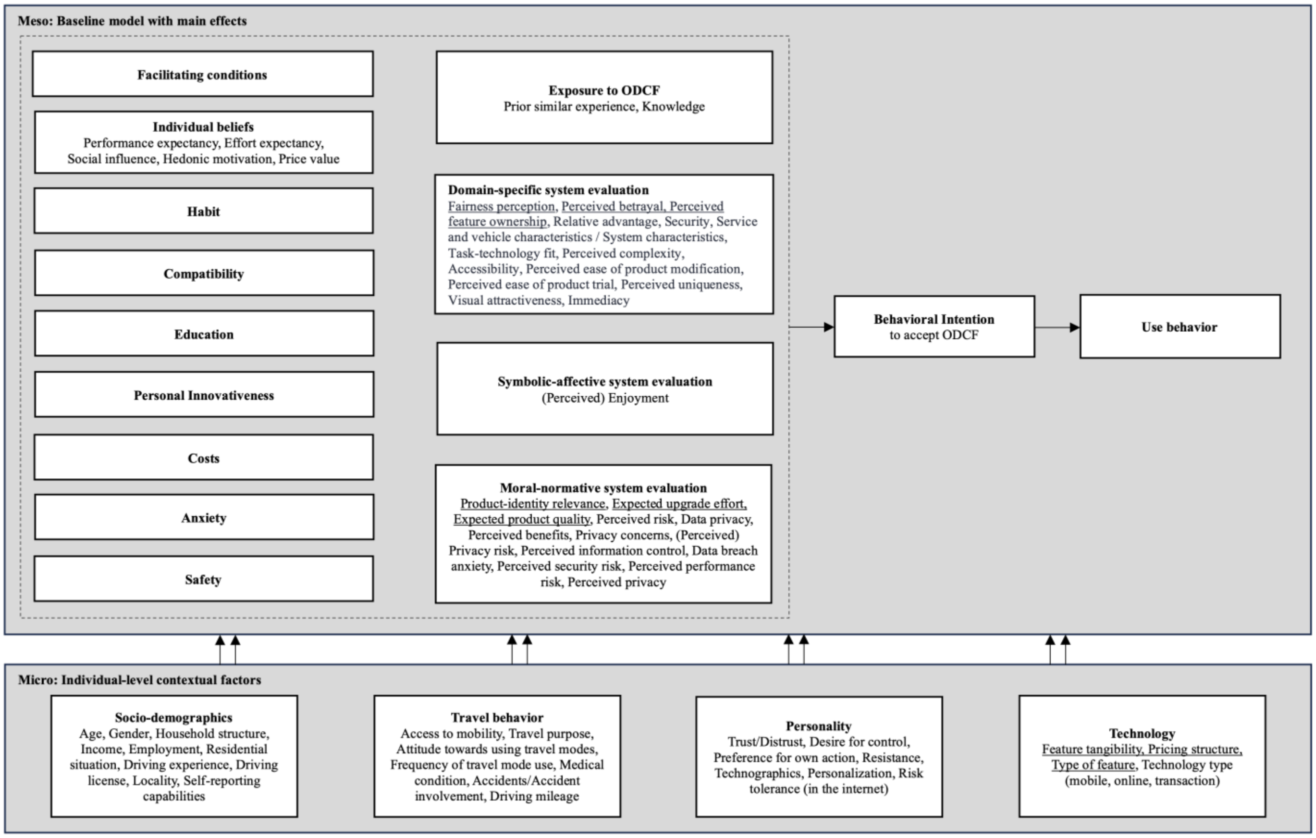

Figure 2. Integrated acceptance model for on-demand car functions
Note: Underlined factors are derived from studies on ODCFs.
Source: Own elaboration

Several studies identified prior similar experience as a relevant determinant towards acceptance of related contexts towards ODCFs. For instance, Kim et al. (2016) investigated user resistance toward acceptance of in-vehicle infotainment (IVI) systems. Contrary to their expectations, the prior similar experience triggered negative perceptions toward IVI systems and is a direct and powerful antecedent for resistance. This outcome could potentially be attributed to the relatively inferior quality of telematics systems that were accessible prior to the current iteration of IVI systems in the market (Kim et al., 2016).

Nordhoff et al. (2020) showed that experience with specific advanced driver assistance systems could positively impact individuals' behavioral intention in the context of conditionally automated cars. For instance, experience with adaptive cruise control was found to have a small positive effect on behavioral intention. However, experience with parking assistance had a small negative impact, possibly due to driver difficulties with using such systems. The findings suggest that the effect of prior experience depends on the specific feature and whether the prior experience with the feature has been positive or negative (Nordhoff et al., 2020). Hence, the feature type could be a relevant moderating factor for investigating the relationship between prior similar experiences and behavioral intention to accept ODCFs.

Razak et al. (2022) investigated the comprehension of in-vehicle applications and identified a positive impact on trust, social influence, and system characteristics. These factors, in turn, contribute to cultivating a positive attitude and greater intention to utilize the application within their driving context. The authors contend that users are more likely to make well-informed decisions when knowledgeable about the applications' merits and

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limitations (Razak et al., 2022). Stiegemeier et al. (2022) evaluated knowledge as drivers who do not know how their system works would need to learn it. In line with the argumentation of Razak et al. (2022) but in other words, they conclude that users will not adopt a technology due to a lack of knowledge about the system (Stiegemeier et al., 2022). Hence, a higher level of knowledge about ODCFs (i.e., benefits, and limitations) would increase the behavioral intention to accept ODCFs.

4.5.1 Domain-specific system evaluation

Numerous studies identify performance expectancy or perceived usefulness as influential in behavioral intention towards ODCFs. Hanesch et al. (2022) observed that performance expectancy significantly impacts behavioral intention for connected car services (Hanesch et al., 2022). Similarly, in the IoV services context, performance expectancy positively affected usage intentions (Liang et al., 2020). This effect was mirrored in the context of autonomous cars (Nordhoff et al., 2020), vehicular services (Walter & Abendroth, 2020), telematics (N. H. Chen, 2019), and other related domains (Razak et al., 2022; Yu & Jin, 2021; Yoon & Cho, 2016). Hence, it can be expected that performance expectancy would positively influence the driver's behavioral intention to acceptance of ODCFs.

Effort expectancy (or "perceived ease of use") showed a positive link to the behavioral intention of autonomous driving acceptance (Garidis et al., 2020), consistent with Leicht et al. (2018). Contrarily, no significant relationship was observed in studies by Cho et al. (2017), Liang et al. (2020), and Nordhoff et al. (2020). Yet, PEOU revealed positive associations with outcomes like attitude or perceived usefulness in other research (N. H. Chen, 2019; Yu & Jin, 2021). Thus, drivers who find ODCFs easier to use tend to have more positive attitudes and a greater willingness to accept them. In contrast, drivers who find ODCFs time-consuming will more likely have negative attitudes.

Regarding facilitation conditions, Park et al. (2013) identified a positive correlation between facilitation conditions and smartphone-car connectivity (Park et al., 2013). Although Liang et al. (2020) found no direct effect on behavioral intention in the context of IoV services, they highlighted its role in conjunction with other conditions (Liang et al., 2020). Nordhoff et al. (2020) did not find facilitation conditions directly influencing behavioral intention for automated cars, but observed significant relationships between effort expectancy and hedonic motivation (Nordhoff et al., 2020). Regarding ODCFs, it would not be expected to find a strong positive influence directly on the behavioral intention to accept. Still, facilitation conditions can positively influence other factors, such as hedonic motivation, directly influencing the driver's acceptance of ODCFs.

Safety is crucial in technology acceptance within vehicles. Osswald et al. (2012) stress the risky nature of limited technology interaction in cars and underscore the influence of perceived safety on drivers' acceptance of in-car information systems (Osswald et al., 2012). Numerous studies have noted safety's impact on the intention to use autonomous driving technologies (Cho et al., 2017; Garidis et al., 2020; Nordhoff et al., 2020). Specifically, Garidis et al. (2020) identified safety as a paramount determinant for autonomous vehicle adoption (Garidis et al., 2020). Stiegemeier et al. (2022) investigated in-vehicle technology acceptance and determined that perceived safety, viewed as potential driving distractions, consistently influences technology adoption in vehicles (Hewitt et al., 2019; Osswald et al., 2012; Trübswetter & Bengler, 2013). They suggest including safety concerns in acceptance models for future investigations (Stiegemeier et al., 2022). Considering the findings of these studies in related contexts of ODCFs, it can be expected that safety will positively influence drivers' acceptance of ODCFs.
Razak et al. (2022) showed system characteristics influence perceived usefulness and ease of use in in-vehicle applications, directly affecting usage intentions (Razak et al., 2022). Chen et al. (2019) integrated TAM with TTF, assessing technology's fit with user tasks in automobile telematics. Telematics products, being relatively new, may make users unfamiliar with benefits, leading to technology characteristics having a more pronounced impact than task characteristics (N. H. Chen, 2019). Thus, system and technology specifics likely influence performance and effort expectancy in ODCFs.

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Several factors can directly influence or explain behavioral intention to accept ODCFs in the domain-specific system evaluation. Hampton-Sosa (2019) studied music product usage in streaming platforms, focusing on the access economy model (Hampton-Sosa, 2019). While not directly addressing vehicle functions, the study centers on the access economy business model, prioritizing user access over product ownership. This aligns with ODCFs, wherein features are pre-installed in the vehicle but require an additional activation fee. The study introduced variables like perceived product format usefulness and ease of product modification. Modern trends allow for easier digital content modification, enhancing consumer engagement (Hampton-Sosa, 2019). Such adaptability in ODCFs can enable users to activate built-in car features, supporting continuous product customization. Hampton-Sosa emphasizes that easier product modification enhances the user-perceived utility and provides more enjoyment opportunities (Hampton-Sosa, 2019). This idea stems from customizable products requiring minimal effort (Hampton-Sosa, 2019; Pavlou & Fygenson, 2006). Concerning product trials, pre-purchase product assessments are crucial (Rogers, 2010). Hampton-Sosa defined this as effortless product evaluation before the acquisition (Hampton-Sosa, 2019). In the context of ODCF, this variable could be relevant since studies found negative perceptions of consumers towards internal product upgrades, which short-term trials could alleviate. Also, trials could contribute to knowledge about a function or system, which in the study of Stiegemeier et al. (2022) was found to be a relevant category: "Many drivers develop an understanding […] mainly through trial and error and experiences with the system" (Stiegemeier et al., 2022, p. 77). Hampton-Sosa's results indicated significant positive correlations between perceived ease of product modification and usefulness and enjoyment. They also found significant influences of product trial ease on usefulness and enjoyment (Hampton-Sosa, 2019). Given this, ease of product modification and trial can likely affect drivers' acceptance of ODCFs.

Other potential endogenous or exogenous mechanisms toward driver's acceptance of ODCFs are security (Garidis et al., 2020), complexity (J. Kim et al., 2016), accessibility (N. Kim et al., 2019), uniqueness (Vafaei-Zadeh et al., 2021), visual attractiveness (Yoon & Cho, 2016), and immediacy (Noraga et al., 2021).

4.5.2 Symbolic-affective system evaluation

Nastjuk et al. (2020) explored autonomous driving acceptance using a TAM-based design, highlighting enjoyment as a key determinant with a positive correlation to perceived ease of use (Nastjuk et al., 2020). Similarly, Chen et al. (2019) emphasized perceived enjoyment as an intrinsic motivator affecting perceived ease of use (N. H. Chen, 2019; Venkatesh, 2000). This suggests that in ODCFs, enjoyment may influence effort expectancy and, thus, driver acceptance.

Subjective norm, defined as one's perception of others' expectations regarding behavior (Fishbein & Ajzen, 1975), was significantly linked to perceived usefulness in autonomous driving by Nastjuk et al. (2020) and as an antecedent for resistance in in-vehicle infotainment systems by Kim et al. (2016). A similar concept of social influence was identified in several studies as significantly impacting acceptance. Notably, Nordhoff et al. (2020) ranked social influence as a primary predictor for using automated cars (Nordhoff et al., 2020). Multiple studies confirm this trend across various in-vehicle technologies, underscoring the importance of social influence in tech acceptance (Adell, 2010; Buckley et al., 2018; Kaye et al., 2020; Panagiotopoulos & Dimitrakopoulos, 2018; Yu & Jin, 2021). For IVIS usage, drivers cited social influences during purchasing but rarely discussed in-drive safety (Oviedo-Trespalacios et al., 2019). Stiegemeier et al. (2022) propose that familial or peer influences may impact vehicle purchase decisions but not the choice to utilize advanced driver assistance systems or IVIS during drives (Stiegemeier et al., 2022). Razak et al. (2022) and Zadeh et al. (2021) also observed significant links between social influence and user attitudes towards in-vehicle applications and dashcams respectively (Razak et al., 2022; Vafaei-Zadeh et al., 2021). Walter & Abendroth (2020) found social norms impacted intentions concerning connected vehicular services (Walter & Abendroth, 2020). Given its frequent identification across studies, social influence appears pivotal in ODCFs acceptance.

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ISSN 2345-0282 (online) http://jssidoi.org/jesi/
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4.5.3 Moral-normative system evaluation

Walter & Abendroth (2020) examined informational privacy in connected vehicles and developed an acceptance model. Their results highlight the significance of privacy considerations in shaping attitudes towards system use, directly influencing user intentions. Notably, the study emphasized the importance of privacy concerns, privacy risk, and perceived information control in vehicular app acceptance, suggesting measures that enhance personal information control (Walter & Abendroth, 2020). Similarly, Noraga et al. (2021) observed that perceived privacy influenced consumer acceptance of on-demand services due to concerns over personal information exchange (Noraga et al., 2021). Integrating informational privacy variables such as privacy concerns, privacy risk, and perceived information control should lead to relevant findings in the context of ODCF acceptance.

Yu & Cai (2022) investigated factors affecting attitudes towards in-vehicle infotainment data services, incorporating variables like data breach anxiety and various perceived risks. The research identified significant relationships between these variables and users' attitudes, with the most substantial link between data breach anxiety and perceived privacy risk. The findings stress the implications of perceived risks on user attitudes for intelligent connected vehicle data services and emphasize the consequences of data breaches (Yu & Cai, 2022). These insights align with Walter & Abendroth (2020), underscoring the need to consider differentiated risk factors (security, privacy, performance) as predictors e.g., trust, attitude, and behavioral intention in ODCFs.

4.5.4 Socio-demographics

Razak et al. (2022) found that users with limited self-reported capabilities firmly intended to use in-vehicle applications. Urban or suburban residents, gender, and driving experience also influenced intentions, but age had inconclusive effects (Razak et al., 2022). Nordhoff et al. (2020) identified age and gender as having minor effects on the intention to use automated cars (Nordhoff et al., 2020). Factors like household structure and residential location affected support for autonomous vehicles, with urban residents showing higher support (Hudson et al., 2019). Positive associations were identified between having children, higher income levels, higher education, and acceptance of vehicle automation, but negative associations were observed among the unemployed or retired (Bansal et al., 2016; Nazari et al., 2018; Kyriakidis et al., 2015; Liu et al., 2019; Hudson et al., 2019). These insights suggest that factors like self-reported capabilities and residential location could directly, indirectly, or moderating influence the acceptance of ODCFs by drivers.

4.5.5 Travel behavior

Users involved in road accidents show a greater intention to use in-vehicle applications (Razak et al., 2022). Nordhoff et al. (2019) confirmed the relevance of travel behavior for automated vehicle acceptance (Nordhoff et al., 2019). Licensed drivers were less likely to use shared autonomous vehicles (Bansal et al., 2016). A positive link exists between driving extent and willingness to pay for autonomous vehicles (Kyriakidis et al., 2015). However, driving distance or experience doesn't notably influence in-vehicle app acceptance (Razak et al., 2022). Individuals with more accident experiences tended to embrace automated vehicles (Bansal et al., 2016). Commuting modes correlate with self-driving vehicle use preferences; private car drivers were more reluctant than public transport users or pedestrians (Zmud & Sener, 2017). Ride-sourcing users and carsharing subscribers favored demand-responsive travel modes over traditional driving (Winter et al., 2017). Given the insights derived from the acceptance of autonomous vehicles, it is plausible to anticipate that various factors linked to travel behavior may exhibit moderating effects on the associations between variables elucidating the acceptance of ODCFs.

4.5.6 Personality

Trust is a key determinant in user acceptance of ODCFs (Chan & Lee, 2021; Cho et al., 2017; Liang et al., 2020; Nastjuk et al., 2020; Razak et al., 2022; Stiegemeier et al., 2022; Vafaei-Zadeh et al., 2021). Initial trust affects the intent to accept IoV-based services (Liang et al., 2020). Trust's significance was emphasized in dashcam adoption and the influence of user perceptions about its safety and usefulness (Razak et al., 2022). Proper trust calibration can increase acceptance (Stiegemeier et al., 2022). Hence, trust is expected to be an essential determinant regarding drivers' acceptance of ODCFs, and higher levels of trust increase the behavioral intention to accept.

High technographic, indicating technological inclination, lead to increased adoption of car connectivity services (Park et al., 2013). Such drivers likely have positive beliefs regarding in-vehicle infotainment systems (J. Kim et al., 2016). Thus, the same is expected for the context of ODCF acceptance because it is an innovative concept that, as expected, is also initially accepted by drivers with an affinity for innovation.

Desire for control negatively influences intentions toward autonomous vehicles (Garidis et al., 2020). In parking assists, some drivers prioritize personal control (Stiegemeier et al., 2022). This factor, alongside "preference for own action," can influence ODCF acceptance.

Personalization significantly impacts the adoption intention of on-demand services (Yeap et al., 2017). Thus, ODCFs that allow for personalization are expected to be well-received.

Resistance affects the intention to use in-vehicle infotainment systems influenced by perceived usefulness, complexity, and risk (J. Kim et al., 2016). Hence, drivers with higher resistance towards ODCFs are expected to be less likely to accept and use ODCFs.

Risk tolerance for online activities is a significant moderator for connected car service adoption (Hanesch et al., 2022), implying higher risk-tolerant drivers might be more accepting of ODCFs.

4.5.7 Technology

This group class pertains to the class of IT artifacts utilized by individual users in their task execution (Burton-Jones & Straub Jr, 2006; Goodhue & Thompson, 1995). Technological attributes encompass collective functionality, distinctive features across various technologies within the same class, and other attributes like usability (Venkatesh et al., 2016). The target technologies, such as enterprise information systems (Neufeld et al., 2007), e-government technologies (Carter & Schaupp, 2008; McLeod et al., 2009; Schaupp et al., 2010), or online collaboration technology (Brown et al., 2010) served as the stimuli for UTAUT extensions in several studies (Venkatesh et al., 2016).

In this present paper, the technology class includes different types of on-demand car functions (i.e., features) as well as the critical characteristics of ODCFs, namely their tangibility and pricing structure (Garbas et al., 2022; Schaefers et al., 2022). Blut et al. (2022) extended technology types by integrating transaction/non-transaction, offline/online dimensions (Meuter et al., 2000) and introducing mobile/non-mobile based on Balasubraman et al. (2002). They emphasized differential behavioral intentions towards transactional technologies due to potential financial risks and associated expectations (Blut et al., 2022). In the context of ODCFs, the differentiation could be relevant depending on the monetization model and whether a free trial is offered. For example, ODCFs can be offered temporarily or unlimited for a fee (transactional), but there is the option for a free trial beforehand (non-transactional). Authors also question these options: “Could free short-term trials backfire or alleviate the negative impact of internal product upgrades?” (Garbas et al., 2022, n. p.). Hence, this factor is closely related to the pricing structure, which already showed relevant effects in studies on ODCFs, e.g., Schaefers et al. (2022).

Different user expectations are proposed for internet versus non-internet technologies (Meuter et al., 2000). The impact of effort expectancy, facilitating conditions, and social influence on behavioral intention and usage will exhibit greater strength for Internet technologies than non-Internet technologies (Blut et al., 2022). In the context of ODCFs, the individual functions differentiate in terms of their software and hardware share (feature tangibility) (Garbas et al., 2022; Schaefers et al., 2022). Thus, on the one side, pure software functions can require a permanent internet connection (i.e., internet, for instance, real-time traffic information). On the other side, pure hardware functions (e.g., heated seats) do not require a permanent internet connection once activated (non-internet). Hence, the factor is related to feature tangibility and type of feature, and different effects of factors such as effort expectancy on behavioral intention to accept ODCFs can be expected for internet versus non-internet technologies.

Regarding mobile and non-mobile technologies, Blut et al. (2022) suggest that while mobile technologies offer increased flexibility (Balasubraman et al., 2002), users' reliance on them due to limited alternatives may strengthen the effects of performance expectancy, effort expectancy, and facilitating conditions on behavioral intention and use, particularly for mobile technologies compared to non-mobile ones. This technology dimension could be related to the different technologies that drivers can use to unlock ODCFs, for instance on a website (non-mobile), on their smartphone (mobile) (Garbas et al., 2022), or directly in the on-board system of the car (mobile) (Petry & Moormann, 2020). Since all these technologies have individual specifics regarding how the user can interact, it can be assumed that drivers' perceptions and behavioral intention to accept ODCF will differentiate depending on the non-mobile versus mobile technology to unlock ODCFs.

Schaefers et al. (2022) found that exposure to intangible ODCFs, like intelligent voice assistants, led to higher purchase intent than tangible ODCFs, such as seat heating. Fairness perceptions affected purchase intentions, favoring intangible ODCFs. These results support feature-dependent consumer responses, favoring software-based intangible features over hardware-based tangible ones (Schaefers et al., 2022). Besides differentiating the types of features based on the tangibility, also other criteria can be used to distinguish types of features from each other:

For instance, the value proposition encompasses the additional value provided to customers, which can address existing problems or fulfill existing needs (Bosler et al., 2018). The value proposition is crucial to customer purchase decisions (Osterwalder & Pigneur, 2010). Consequently, monetising a connected car service becomes unfeasible if customers fail to perceive its benefits (Chanias & Hess, 2016; Piccinini et al., 2015). Sterk et al. (2022) conducted a study that classified the value propositions of connected car services for individual drivers into five broad categories: safety, convenience, cost reduction, traffic efficiency, and infotainment (Sterk et al., 2022). Similar value propositions, tailored to the driver's perspective, have been identified in other studies (Coppola & Morisio, 2016). Additionally, environmental benefit, such as reducing environmental impact, is considered a value proposition or customer benefit in the context of connected vehicle services (Tian et al., 2018). Another dimension to classify connected car services is based on the application's target object type. This classification results from an extensive literature survey by Tian et al. (2018). It adds another dimension with three categories, i.e., vehicle-centric, infrastructure-centric, and traveler-centric (Tian et al., 2018).

Lastly, as part of the IoV architecture, the application layer provides various services and supports novel services and business operating models. The application layer can be classified into closed services (particularly services highly correlated with vehicles aiming to increase driving safety) and open services (mainly provided by third parties to users) (Yang et al., 2017).

These additional three criteria (i.e., value proposition, type of object targeted, and closed/open services) can be used individually or in combination to differentiate the types of features of ODCFs. Existing studies have already achieved different results when types of features are differentiated by feature tangibility (Garbas et al., 2022; Schaefers et al., 2022), so it can be assumed that this also applies to the additional criteria mentioned.

ISSN 2345-0282 (online) http://jssidoi.org/jesi/
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5. Discussion

This study presents an integrated model for driver's acceptance of ODCFs. It is based on a critical literature of studies on ODCFs and acceptance research in related contexts, revealing 74 relevant acceptance factors for the model. The factors are located at two levels, whereby the meso-level merges domain-specific, symbolic-affective, moral-normative factors, and relevant factors retrieved from existing acceptance models. It is influenced by factors at the micro-level, representing individual difference factors (see Figure 2).

This model can be implemented in two distinct ways. Firstly, when the research objective involves understanding the acceptance of ODCFs, the complete model can be employed and tailored to the specific research context. Secondly, when the research objective focuses on explanation or prediction, a partial model can be developed by incorporating relevant individual factors from both levels to align with the individual context. This procedure is also suggested by Venkatesh et al. (2016), who recommend theorizing cross-level influences and conducting multi-level research to examine the impacts of contextual factors empirically. Furthermore, they recommend considering new conceptualizations of technology acceptance and use (Venkatesh et al., 2016), i.e., the usage behavior in the presented model.

Some studies in the context of ODCFs incorporate different consumer responses such as willingness-to-pay (Garbas et al., 2022), loyalty intentions (Garbas et al., 2022), or purchase intentions (Garbas et al., 2022; Schaefers et al., 2022; Wiegand & Imschloss, 2021). Based on the recommendations of Venkatesh et al. (2016) and the different consumer responses in the context of ODCFs, a simple multi-level model that reflects the recommendations discussed before can be derived (see Figure 3).

It conceptualizes that fairness perception and expected product quality positively influence behavioural intention to accept ODCFs, while perceived betrayal and expected upgrade efforts negatively impact driver's acceptance. The feature's tangibility moderates these relationships. Finally, the behavioral intention to accept has a positive effect on the driver's purchase intention of ODCFs.

This exemplary partial model (Figure 3) is deduced from the comprehensive model (Figure 2) following cross-level theorizing and offering new conceptions of relevant factors. Both models have been originally conceptionalized within this study, drawing upon corresponding literature and potential acceptance criteria pertaining to driver's acceptance of ODCFs.

In forthcoming research endeavors, the respective acceptance critera can serve as foundation for developing appropriate constucts and formulating hypotheses. The novelty of these figures lies in their collective establishment of an inclusive, multi-dimensional model, synthesizing established theories and empirical findings and encompassing diverse factors within a structured framework. Practically, this innovative approach provides a roadmap for researchers and practitioners, facilitating nuanced understanding and enhanced decision-making concerning the acceptance and implementation of ODCFs.

ISSN 2345-0282 (online) http://jssidoi.org/jesi/
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http://doi.org/10.9770/jesi.2023.11.1(8)

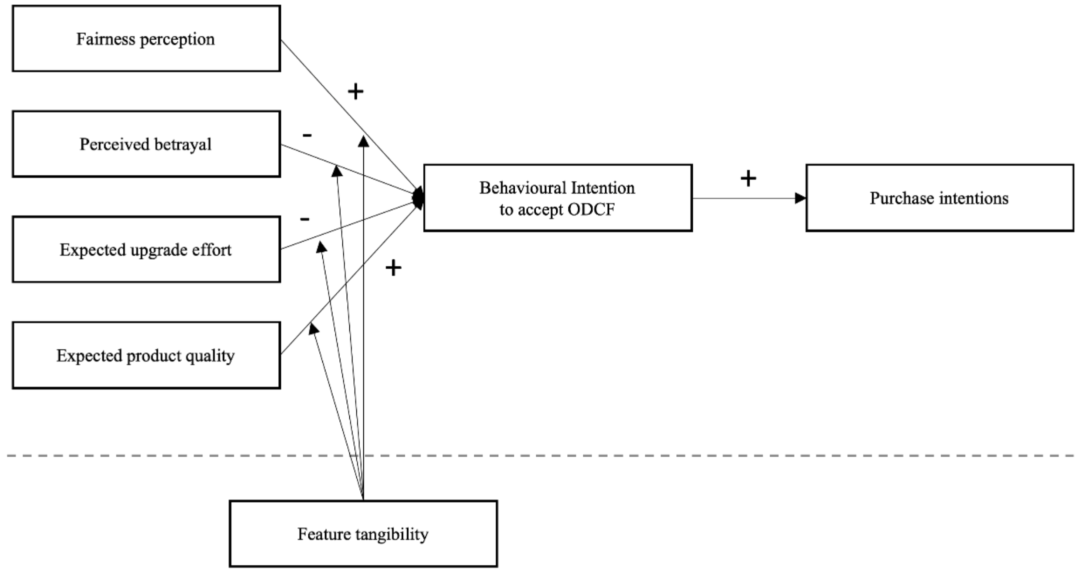

Figure 3. Impact of ODCF factors on acceptance and purchase intentions moderated by feature tangibility
Source: Own elaboration

Prior studies have predominantly employed linear regression analyses to assess the associations between acceptance factors and the acceptance construct. Multivariate analysis methods like regression or structural equation modeling can quantify mathematical relationships among model factors. Qualitative approaches like focus groups and interviews can complement the model by identifying new factors. The model also elucidates causal relationships among factors. Thus, future research should adopt longitudinal and experimental designs to explore causal relationships (Nordhoff et al., 2019).

The strength of the integrated acceptance model for ODCFs is its profound ground in empirical research; however, the current state of the research on the specific topic of ODCFs is limited. More specifically, no research is available on drivers' acceptance of ODCFs. Due to that, mainly acceptance research in contexts related to ODCFs has been used to develop the model. This is associated with uncertainty about the extent to which the results of the studies in other contexts can be applied to ODCFs. ODCFs are primarily about a new business model or service concept and only secondarily about the actual function of the connected vehicle. The few existing studies in the ODCF context have already identified individual factors (e.g., fairness perception, perceived betrayal) that take this distinction into account and focus on the main aspect of ODCFs, which is the service offering concept.

In contrast, the studies from the related contexts are predominantly concerned with the content or the actual functions and not about how to access the functions. In a sense, they start at a later point in the value chain and assume that the function is available to the driver without any further action, which means that the function content is the primary decision criterion for the driver's acceptance. In addition, there are challenges within this content research; for example, in the context of autonomous driving functions, the authors mention that respondents lack knowledge of experience with autonomous vehicles, which may threaten the validity of results (Fraedrich & Lenz, 2014). This can be transferred to the ODCFs context, which as a service innovation is still in an early stage of adoption where respondents lack experience with the concept and how this technology can form a part of their lives in the short- and middle-run.

Therefore, further studies should focus on identifying specific driver acceptance criteria about the activation and offering model of vehicle functions and to differentiate the activation from usage more clearly using a process. This can be approached by considering industries such as music-/video-streaming, or car-sharing, where the on-demand concept is more established. The literature review identifies various factors associated with ODCFs, warranting further validation or extension via empirical research. Due to the inclusion of multiple factors, the model's complexity may hinder its application, even though streamlined factors often provide significant explanatory power (Nordhoff et al., 2019). Yet, the model permits factor extraction for empirical methods, e.g., hierarchical linear models (Venkatesh et al., 2016). It predominantly addresses micro- and meso-levels, neglecting macro aspects like environment or organization, necessitating a broader focus in future research (Nordhoff et al., 2019; Venkatesh et al., 2016). Additionally, factor weightage is absent, but as Ajzen and Fishbein (2005) suggest, this could vary based on the behavior and audience studied (Ajzen & Fishbein, 2005; Nordhoff et al., 2019).

6. Conclusions

This study introduces an integrated multi-level model to predict drivers' acceptance of on-demand car functions (ODCFs). Rooted in the UTAUT and CTAM frameworks, this model amalgamates pertinent acceptance factors derived from extensive research concerning ODCFs and related domains. A comprehensive set of seventy-four acceptance factors is delineated across micro and meso levels. The meso-level encapsulates factors encompassing the baseline model, antecedents to domain-specific, symbolic-affective, and moral-normative elements, and user exposure to preceding ODCFs. Meanwhile, the micro-level involves individual difference factors such as socio-demographics, travel behavior, personality, and technology affinity, influencing the meso-level factors. The model serves to enrich both researchers and practitioners engaged in ODCF implementation. To fortify the model's robustness and utility, future endeavors should encompass empirical validation, potential model adaptations, in-depth exploration of factor nuances and interconnections, and potentially employ longitudinal or experimental studies to accomplish these goals.

References

Abd Aziz, S. (2016). Does fear of new car technologies influence brand loyalty relationship. *Journal of Marketing Management*, *4*(1), 125–136. https://doi.org/10.15640/jmm.v4n1a12

Adell, E. (2010). Acceptance of driver support systems. *Proceedings of the European Conference on Human Centred Design for Intelligent Transport Systems*, *2*, 475–486

Adnan, N., Nordin, S. M., bin Bahruddin, M. A., & Ali, M. (2018). How trust can drive forward the user acceptance to the technology? In-vehicle technology for autonomous vehicle. *Transportation Research Part A: Policy and Practice*, *118*, 819–836. https://doi.org/10.1016/j.tra.2018.10.019

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I., & Fishbein, M. (2005). The influence of attitudes on behavior. *The Handbook of Attitudes*, *173*(221), 31.

Atasoy, O., & Morewedge, C. K. (2018). Digital goods are valued less than physical goods. *Journal of Consumer Research*, *44*(6), 1343–1357. https://doi.org/10.1093/jcr/ucx102

Balasubraman, S., Peterson, R. A., & Jarvenpaa, S. L. (2002). Exploring the implications of m-commerce for markets and marketing. *Journal of the Academy of Marketing Science*, *30*(4), 348–361. https://doi.org/10.1177/009207002236910

Bansal, P., Kockelman, K. M., & Singh, A. (2016). Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. *Transportation Research Part C: Emerging Technologies*, *67*, 1–14. https://doi.org/10.1016/j.trc.2016.01.019

Blodgett, J. G., Hill, D. J., & Tax, S. S. (1997). The effects of distributive, procedural, and interactional justice on postcomplaint behavior. *Journal of Retailing*, *73*(2), 185–210. https://doi.org/10.1016/s0022-4359(97)90003-8

Blut, M., Chong, A. Y. L., Tsigna, Z., & Venkatesh, V. (2022). Meta-Analysis of the Unified Theory of Acceptance and Use of Technology (UTAUT): Challenging its Validity and Charting a Research Agenda in the Red Ocean. *Journal of the Association for Information Systems*, *23*(1), 13–95. https://doi.org/10.17705/1jais.00719

Bosler, M., Burr, W., & Ihring, L. (2018). Vernetzte Fahrzeuge – empirische Analyse digitaler Geschäftsmodelle für Connected-Car-Services. *HMD Praxis Der Wirtschaftsinformatik*, *55*(2), 329–348. https://doi.org/10.1365/s40702-018-0396-8

Brown, S. A., Dennis, A. R., & Venkatesh, V. (2010). Predicting collaboration technology use: Integrating technology adoption and collaboration research. *Journal of Management Information Systems*, *27*(2), 9–54. https://doi.org/10.2139/ssrn.4061120

Buckley, L., Kaye, S.-A., & Pradhan, A. K. (2018). Psychosocial factors associated with intended use of automated vehicles: A simulated driving study. *Accident Analysis & Prevention*, *115*, 202–208. https://doi.org/10.1016/j.aap.2018.03.021

Burton-Jones, A., & Straub Jr, D. W. (2006). Reconceptualizing system usage: An approach and empirical test. *Information Systems Research*, *17*(3), 228–246. https://doi.org/10.1287/isre.1060.0096

Carter, L., & Schaupp, L. C. (2008). Efficacy and acceptance in e-file adoption. *AMCIS 2008 Proceedings*, 320. https://doi.org/10.4018/978-1-60960-162-1.ch015

Chan, W. M., & Lee, J. W. C. (2021). 5g connected autonomous vehicle acceptance: the mediating effect of trust in the technology acceptance model. *Asian Journal of Business Research*, *11*(1). https://doi.org/10.14707/ajbr.210098

Chanias, S., & Hess, T. (2016). *Understanding digital transformation strategy formation: Insights from Europe's automotive industry*. http://aisel.aisnet.org/pacis2016/296

Chen, C.-F. (2019). Factors affecting the decision to use autonomous shuttle services: Evidence from a scooter-dominant urban context. *Transportation Research Part F: Traffic Psychology and Behaviour*, *67*, 195–204. https://doi.org/10.1016/j.trf.2019.10.016

Chen, N. H. (2019). Extending a TAM–TTF model with perceptions toward telematics adoption. *Asia Pacific Journal of Marketing and Logistics*, *31*(1), 37–54. https://doi.org/10.1108/APJML-02-2018-0074

Cho, Y., Park, J., Park, S., & Jung, E. S. (2017). Technology Acceptance Modeling based on User Experience for Autonomous Vehicles Corresponding Author. *Journal of the Ergonomics Society of Korea*, *36*(2), 87–108. https://doi.org/10.5143/JESK.2017.36.2.87

Christensen, C. M. (2011). *The innovator's dilemma: Warum etablierte Unternehmen den Wettbewerb um bahnbrechende Innovationen verlieren*. Vahlen. https://doi.org/10.15358/9783800642816-239

Compeau, D., Higgins, C. A., & Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS Quarterly*, 145–158. https://doi.org/10.2307/249749

Coppola, R., & Morisio, M. (2016). Connected car: Technologies, issues, future trends. *ACM Computing Surveys*, *49*(3). https://doi.org/10.1145/2971482

Cziehso, G. P., Schaefers, T., & Kukar-Kinney, M. (2019). Free no more-investigating customer reactions to unexpected free-to-fee switches. *Journal of Business Research*, *101*, 229–242. https://doi.org/10.1016/j.jbusres.2019.03.050

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. Massachusetts Institute of Technology. http://hdl.handle.net/1721.1/15192

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319–340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace 1. *Journal of Applied Social Psychology*, *22*(14), 1111–1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. https://doi.org/10.2307/2065853

Fraedrich, E., & Lenz, B. (2014). Automated Driving. *Transportation Research Record: Journal of the Transportation Research Board*, *2416*(1), 64–72. https://doi.org/10.3141/2416-08

Garbas, J., Schubach, S., Mende, M., Scott, M. L., & Schumann, J. H. (2022). You want to sell this to me twice!? How perceptions of betrayal may undermine internal product upgrades. *Journal of the Academy of Marketing Science*. https://doi.org/10.1007/s11747-022-00881-8

Garidis, K., Ulbricht, L., Rossmann, A., & Schmäh, M. (2020). Toward a User Acceptance Model of Autonomous Driving. *Proceedings of the 53rd Hawaii International Conference on System Sciences*. http://hdl.handle.net/10125/63909

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 213–236. https://doi.org/10.2307/249689

Grégoire, Y., & Fisher, R. J. (2008). Customer betrayal and retaliation: when your best customers become your worst enemies. *Journal of the Academy of Marketing Science*, *36*, 247–261. https://doi.org/10.1007/s11747-007-0054-0

Hampton-Sosa, W. (2019). The Access Model for Music and the Effect of Modification, Trial, and Sharing Usage Rights on Streaming Adoption and Piracy. *Journal of Theoretical and Applied Electronic Commerce Research*, *14*(3), 126–155. https://doi.org/10.4067/s0718-18762019000300108

Hanesch, A., Brune, P., & Gewald, H. (2022). Will They Like It? – Understanding Customer Adoption of Connected Car Services within Automotive Aftersales. *Lecture Notes in Information Systems and Organisation*, *57 LNISO*, 103–117. https://doi.org/10.1007/978-3-031-10902-7_8

Herrenkind, B., Nastjuk, I., Brendel, A. B., Trang, S., & Kolbe, L. M. (2019). Young people's travel behavior–Using the life-oriented approach to understand the acceptance of autonomous driving. *Transportation Research Part D: Transport and Environment*, *74*, 214–233. https://doi.org/10.1016/j.trd.2019.07.023

Hewitt, C., Politis, I., Amanatidis, T., & Sarkar, A. (2019). Assessing public perception of self-driving cars: The autonomous vehicle acceptance model. *Proceedings of the 24th International Conference on Intelligent User Interfaces*, 518–527. https://doi.org/10.1145/3301275.3302268

Hill, C. W. L., & Rothaermel, F. T. (2003). The performance of incumbent firms in the face of radical technological innovation. *Academy of Management Review*, *28*(2), 257–274. https://doi.org/10.2307/30040712

Hudson, J., Orviska, M., & Hunady, J. (2019). People's attitudes to autonomous vehicles. *Transportation Research Part A: Policy and Practice*, *121*, 164–176. https://doi.org/10.1016/j.tra.2018.08.018

Juehling, E., Torney, M., Herrmann, C., & Droeder, K. (2010). Integration of automotive service and technology strategies. *CIRP Journal of Manufacturing Science and Technology*, *3*(2), 98–106. https://doi.org/10.1016/j.cirpj.2010.02.002

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. https://doi.org/10.1016/j.jengtecman.2018.04.006

Kaye, S.-A., Lewis, I., Forward, S., & Delhomme, P. (2020). A priori acceptance of highly automated cars in Australia, France, and Sweden: A theoretically-informed investigation guided by the TPB and UTAUT. *Accident Analysis & Prevention*, *137*, 105441. https://doi.org/10.1016/j.aap.2020.105441

Kim, J., Kim, S., & Nam, C. (2016). User resistance to acceptance of In-Vehicle Infotainment (IVI) systems. *Telecommunications Policy*, *40*(9), 919–930. https://doi.org/10.1016/j.telpol.2016.07.006

Kim, N., Park, Y., & Lee, D. (2019). Differences in consumer intention to use on-demand automobile-related services in accordance with the degree of face-to-face interactions. *Technological Forecasting and Social Change*, *139*, 277–286. https://doi.org/10.1016/j.techfore.2018.11.014

Kwon, S., Ha, S., & Kowal, C. (2017). How online self-customization creates identification: Antecedents and consequences of consumer-customized product identification and the role of product involvement. *Computers in Human Behavior*, *75*, 1–13. https://doi.org/10.1016/j.chb.2017.04.051

Kyriakidis, M., Happee, R., & de Winter, J. C. F. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation Research Part F: Traffic Psychology and Behaviour*, *32*, 127–140. https://doi.org/10.2139/ssrn.2506579

Lee, C., Ward, C., Raue, M., D'Ambrosio, L., & Coughlin, J. F. (2017). Age differences in acceptance of self-driving cars: A survey of perceptions and attitudes. *Human Aspects of IT for the Aged Population. Aging, Design and User Experience: Third International*

Conference, ITAP 2017, Held as Part of HCI International 2017, Vancouver, BC, Canada, July 9-14, 2017, Proceedings, Part I 3, 3–13. https://doi.org/10.1007/978-3-319-58530-7_1

Lee, Y., Kozar, K. A., & Larsen, K. R. T. (2003). The technology acceptance model: Past, present, and future. *Communications of the Association for Information Systems*, *12*(1), 50. https://doi.org/10.17705/1cais.01250

Leicht, T., Chtourou, A., & Ben Youssef, K. (2018). Consumer innovativeness and intentioned autonomous car adoption. *Journal of High Technology Management Research*, *29*(1), 1–11. https://doi.org/10.1016/j.hitech.2018.04.001

Li, W., Wu, G., Yao, D., Zhang, Y., Barth, M. J., & Boriboonsomsin, K. (2021). Stated acceptance and behavioral responses of drivers towards innovative connected vehicle applications. *Accident Analysis and Prevention*, *155*. https://doi.org/10.1016/j.aap.2021.106095

Liang, Y., Zhang, G., Xu, F., & Wang, W. (2020). User Acceptance of Internet of Vehicles Services: Empirical Findings of Partial Least Square Structural Equation Modeling (PLS-SEM) and Fuzzy Sets Qualitative Comparative Analysis (fsQCA). *Mobile Information Systems*, *2020*. https://doi.org/10.1155/2020/6630906

Liu, P., Guo, Q., Ren, F., Wang, L., & Xu, Z. (2019). Willingness to pay for self-driving vehicles: Influences of demographic and psychological factors. *Transportation Research Part C: Emerging Technologies*, *100*, 306–317. https://doi.org/10.1016/j.trc.2019.01.022

Ma, Z., Gill, T., & Jiang, Y. (2015). Core versus Peripheral Innovations: The Effect of Innovation Locus on Consumer Adoption of New Products. *Journal of Marketing Research*, *52*(3), 309–324. https://doi.org/10.1509/jmr.13.0337

Madigan, R., Louw, T., Wilbrink, M., Schieben, A., & Merat, N. (2017). What influences the decision to use automated public transport? Using UTAUT to understand public acceptance of automated road transport systems. *Transportation Research Part F: Traffic Psychology and Behaviour*, *50*, 55–64. https://doi.org/10.1016/j.trf.2017.07.007

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, *13*(3), 334–359. https://doi.org/10.1287/isre.13.3.334.81

McLeod, A., Pippin, S., & Catania, V. (2009). Using technology acceptance theory to model individual differences in tax software use. *AMCIS 2009 Proceedings. 811*. http://aisel.aisnet.org/amcis2009/811

Meuter, M. L., Ostrom, A. L., Roundtree, R. I., & Bitner, M. J. (2000). Self-service technologies: understanding customer satisfaction with technology-based service encounters. *Journal of Marketing*, *64*(3), 50–64. https://doi.org/10.1509/jmkg.64.3.50.18024

Najm, W., Stearns, M., Howarth, H., Koopmann, J., Hitz, J. S., & others. (2006). Evaluation of an automotive rear-end collision avoidance system. https://rosap.ntl.bts.gov/view/dot/4307

Namkung, Y., & Jang, S. S. (2009). The effects of interactional fairness on satisfaction and behavioral intentions: Mature versus non-mature customers. *International Journal of Hospitality Management*, *28*(3), 397–405. https://doi.org/10.1016/j.ijhm.2008.11.001

Nastjuk, I., Herrenkind, B., Marrone, M., Brendel, A. B., & Kolbe, L. M. (2020). What drives the acceptance of autonomous driving? An investigation of acceptance factors from an end-user's perspective. *Technological Forecasting and Social Change*, *161*. https://doi.org/10.1016/j.techfore.2020.120319

Nazari, F., Noruzoliaee, M., & Mohammadian, A. K. (2018). Shared versus private mobility: Modeling public interest in autonomous vehicles accounting for latent attitudes. *Transportation Research Part C: Emerging Technologies*, *97*, 456–477. https://doi.org/10.1016/j.trc.2018.11.005

Neufeld, D. J., Dong, L., & Higgins, C. (2007). Charismatic leadership and user acceptance of information technology. *European Journal of Information Systems*, *16*, 494–510. https://doi.org/10.1057/palgrave.ejis.3000682

Ng, I. C. L., & Wakenshaw, S. Y. L. (2017). The Internet-of-Things: Review and research directions. *International Journal of Research in Marketing*, *34*(1), 3–21. https://doi.org/10.1016/j.ijresmar.2016.11.003

Nguyen, B., & others. (2013). Retail fairness: Exploring consumer perceptions of fairness towards retailers' marketing tactics. *Journal of Retailing and Consumer Services*, *20*(3), 311–324. https://doi.org/10.1016/j.jretconser.2013.02.001

Noraga, D., Batu, L., & Alversia, Y. (2021). UTAUT2 Analysis on the Use of On-Demand Services Application with Perceived Privacy as Moderating Effect. *In Proceedings of the 5th Global Conference on Business, Management and Entrepreneurship (GCBME 2020). 5th Global Conference on Business, Management and Entrepreneurship (GCBME 2020). Atlantis Press.* https://doi.org/10.2991/aebmr.k.210831.104

Nordhoff, S., De Winter, J., Kyriakidis, M., Van Arem, B., & Happee, R. (2018). Acceptance of driverless vehicles: Results from a large cross-national questionnaire study. *Journal of Advanced Transportation* https://doi.org/10.1155/2018/5382192

Nordhoff, S., Kyriakidis, M., van Arem, B., & Happee, R. (2019). A multi-level model on automated vehicle acceptance (MAVA): a review-based study. *Theoretical Issues in Ergonomics Science*, *20*(6), 682–710. https://doi.org/10.1080/1463922X.2019.1621406

Nordhoff, S., Louw, T., Innamaa, S., Lehtonen, E., Beuster, A., Torrao, G., Bjorvatn, A., Kessel, T., Malin, F., Happee, R., & Merat, N. (2020). Using the UTAUT2 model to explain public acceptance of conditionally automated (L3) cars: A questionnaire study among 9,118 car drivers from eight European countries. *Transportation Research Part F: Traffic Psychology and Behaviour*, *74*, 280–297. https://doi.org/10.1016/j.trf.2020.07.015

Nordhoff, S., Van Arem, B., & Happee, R. (2016). Conceptual model to explain, predict, and improve user acceptance of driverless podlike vehicles. *Transportation Research Record*, *2602*(1), 60–67. https://doi.org/10.3141/2602-08

Osswald, S., Wurhofer, D., Trösterer, S., Beck, E., & Tscheligi, M. (2012). Predicting information technology usage in the car. *Proceedings of the 4th International Conference on Automotive User Interfaces and Interactive Vehicular Applications - AutomotiveUI '12*, 51. https://doi.org/10.1145/2390256.2390264

Osterwalder, A., & Pigneur, Y. (2010). *Business model generation: A Handbook for Visionaries, Game Changers, and Challengers.* John Wiley & Sons.

Oviedo-Trespalacios, O., Nandavar, S., & Haworth, N. (2019). How do perceptions of risk and other psychological factors influence the use of in-vehicle information systems (IVIS)? *Transportation Research Part F: Traffic Psychology and Behaviour*, *67*, 113–122. https://doi.org/10.1016/j.trf.2019.10.011

Panagiotopoulos, I., & Dimitrakopoulos, G. (2018). An empirical investigation on consumers' intentions towards autonomous driving. *Transportation Research Part C: Emerging Technologies*, *95*, 773–784. https://doi.org/10.1016/j.trc.2018.08.013

Park, J., Kim, J., Nam, C., & Kim, S. (2013). Driver's Intention to Use Smartphone-Car Connectivity. In *Technology, Investment and Uncertainty*. International Telecommunications Society. http://hdl.handle.net/10419/88467

Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. *MIS Quarterly*, 115–143. https://doi.org/10.2307/25148720

Peck, J., & Shu, S. B. (2009). The effect of mere touch on perceived ownership. *Journal of Consumer Research*, *36*(3), 434–447. https://doi.org/10.1086/598614

Petry, L. F., & Moormann, J. (2020). Mobile Payment in the Connected Car: Developing Services Based on Process Thinking. *Business Systems Research*, *11*(3), 63–77. https://doi.org/10.2478/bsrj-2020-0027

Piccinini, E., Hanelt, A., Gregory, R.W., & Kolbe, L.M. (2015). Transforming Industrial Business: The Impact of Digital Transformation on Automotive Organizations. *International Conference on Interaction Sciences*. https://api.semanticscholar.org/CorpusID:16956865

Pierce, J. L., Kostova, T., & Dirks, K. T. (2003). The state of psychological ownership: Integrating and extending a century of research. *Review of General Psychology*, *7*(1), 84–107. https://doi.org/10.1037/1089-2680.7.1.84

Raddats, C., Kowalkowski, C., Benedettini, O., Burton, J., & Gebauer, H. (2019). Servitization: A contemporary thematic review of four major research streams. *Industrial Marketing Management*, *83*, 207–223. https://doi.org/10.1016/j.indmarman.2019.03.015

Razak, S. F. A., Yogarayan, S., Abdullah, M. F. A., & Azman, A. (2022). Modeling User Acceptance of In-Vehicle Applications for Safer Road Environment. *Future Internet*, *14*(5). https://doi.org/10.3390/fi14050148

Rogers, E. M. (2010). *Diffusion of innovations, 4th Edition*. Simon and Schuster.

Schaefers, T., Leban, M., & Vogt, F. (2022). On-demand features: Consumer reactions to tangibility and pricing structure. *Journal of Business Research*, *139*, 751–761. https://doi.org/10.1016/j.jbusres.2021.09.054

Schaupp, L. C., Carter, L., & McBride, M. E. (2010). E-file adoption: A study of US taxpayers' intentions. *Computers in Human Behavior*, *26*(4), 636–644. https://doi.org/10.1016/j.chb.2009.12.017

Seeger, G., & Bick, M. (2013). Mega and Consumer Trends - Towards Car-independent Mobile Applications. *2013 International Conference on Mobile Business*. 27. https://aisel.aisnet.org/icmb2013/27/

Souders, D., & Charness, N. (2016). Challenges of older drivers' adoption of advanced driver assistance systems and autonomous vehicles. *Human Aspects of IT for the Aged Population. Healthy and Active Aging: Second International Conference, ITAP 2016, Held as Part of HCI International 2016 Toronto, ON, Canada, July 17–22, 2016, Proceedings, Part II 2*, 428–440. https://doi.org/10.1007/978-3-319-39949-2_41

Sterk, F., Dann, D., & Weinhardt, C. (2022). *Monetizing Car Data: A Literature Review on Data-Driven Business Models in the Connected Car Domain*. https://hdl.handle.net/10125/79581

Stiegemeier, D., Bringeland, S., Kraus, J., & Baumann, M. (2022). "Do I really need it?": An explorative study of acceptance and usage of in-vehicle technology. *Transportation Research Part F: Traffic Psychology and Behaviour*, *84*, 65–82. https://doi.org/10.1016/j.trf.2021.11.011

Svangren, M. K., Skov, M. B., & Kjeldskov, J. (2017). The connected car: an empirical study of electric cars as mobile digital devices. *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services*, 1–12. https://doi.org/10.1145/3098279.3098535

Tian, D., Wu, G., Boriboonsomsin, K., & Barth, M. J. (2018). Performance Measurement Evaluation Framework and Co-Benefit\/Tradeoff Analysis for Connected and Automated Vehicles (CAV) Applications: A Survey. *IEEE Intelligent Transportation Systems Magazine*, *10*(3), 110–122. https://doi.org/10.1109/MITS.2018.2842020

Trübswetter, N., & Bengler, K. (2013). Why should I use ADAS? Advanced driver assistance systems and the elderly: knowledge, experience and usage barriers. *Driving Assesment Conference*, *7*(2013). https://doi.org/10.17077/drivingassessment.1532

Ülkü, S., Dimofte, C. V, & Schmidt, G. M. (2012). Consumer valuation of modularly upgradeable products. *Management Science*, *58*(9), 1761–1776. https://doi.org/10.1287/mnsc.1120.1519

Vafaei-Zadeh, A., Ng, S.-X., Hanifah, H., Teoh, A. P., & Nawaser, K. (2021). Safety Technology Adoption: Predicting Intention to Use Car Dashcams in an Emerging Country. *International Journal of Innovation and Technology Management*, *18*(05). https://doi.org/10.1142/S021987702150022X

Venkatesh, Morris, Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research*, *11*(4), 342–365. https://doi.org/10.2139/ssrn.4062395

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*, 157–178. https://doi.org/10.2307/41410412

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems, 17*(5), 328–376. https://doi.org/10.17705/1jais.00428

Walter, J., & Abendroth, B. (2020). On the role of informational privacy in connected vehicles: A privacy-aware acceptance modelling approach for connected vehicular services. *Telematics and Informatics*, *49*. https://doi.org/10.1016/j.tele.2020.101361

Wiegand, N., & Imschloss, M. (2021). Do You Like What You (Can't) See? The Differential Effects of Hardware and Software Upgrades on High-Tech Product Evaluations. *Journal of Interactive Marketing*, *56*, 18–40. https://doi.org/10.1016/j.intmar.2021.03.004

Winter, K., Cats, O., Martens, K., & van Arem, B. (2017). A stated-choice experiment on mode choice in an era of free-floating carsharing and shared autonomous vehicles. *TRB 96th Annual Meeting Compendium of Papers*. https://doi.org/10.1109/mtits.2017.8005630

Xia, L., Monroe, K. B., & Cox, J. L. (2004). The price is unfair! A conceptual framework of price fairness perceptions. *Journal of Marketing*, *68(*4), 1–15. https://doi.org/10.1509/jmkg.68.4.1.42733

Xiao, Y., & Watson, M. (2019). Guidance on Conducting a Systematic Literature Review. *Journal of Planning Education and Research*, *39*(1), 93–112. SAGE Publications Inc. https://doi.org/10.1177/0739456X17723971

Xu, Z., Zhang, K., Min, H., Wang, Z., Zhao, X., & Liu, P. (2018). What drives people to accept automated vehicles? Findings from a field experiment. *Transportation Research Part C: Emerging Technologies*, *95*, 320–334. https://doi.org/10.1016/j.trc.2018.07.024

Yang, F., Li, J., Lei, T., & Wang, S. (2017). Architecture and key technologies for Internet of Vehicles: a survey. *Journal of Communications and Information Networks*, *2*(2), 1–17. https://doi.org/10.1007/s41650-017-0018-6

Yeap, J. A. L., Yapp, E. H. T., & Balakrishna, C. (2017). User acceptance of on-demand services. *2017 International Conference on Research and Innovation in Information Systems (ICRIIS)*, 1–6. https://doi.org/10.1109/icriis.2017.8002535

Yoon, S. Bin, & Cho, E. (2016). Convergence adoption model (CAM) in the context of a smart car service. *Computers in Human Behavior*, *60*, 500–507. https://doi.org/10.1016/j.chb.2016.02.082

Yu, Z., & Cai, K. (2022). Perceived Risks toward In-Vehicle Infotainment Data Services on Intelligent Connected Vehicles. *Systems*, *10*(5). https://doi.org/10.3390/systems10050162

Yu, Z., & Jin, D. (2021). Determinants of users' attitude and intention to intelligent connected vehicle infotainment in the 5g-v2x mobile ecosystem. *International Journal of Environmental Research and Public Health*, *18*(19). https://doi.org/10.3390/ijerph181910069

Zhang, B., de Winter, J., Varotto, S., Happee, R., & Martens, M. (2019). Determinants of take-over time from automated driving: A meta-analysis of 129 studies. *Transportation Research Part F: Traffic Psychology and Behaviour*, *64*, 285–307. https://doi.org/10.1016/j.trf.2019.04.020

Zmud, J. P., & Sener, I. N. (2017). Towards an understanding of the travel behavior impact of autonomous vehicles. *Transportation Research Procedia*, *25*, 2500–2519. https://doi.org/10.1016/j.trpro.2017.05.281

Data Availability Statement: More data may be obtained from the authors on a reasonable request.

Author Contributions: Conceptualization: *Tom Graesner*; methodology: *Tom Graesner*, *Roland Vogt*; data analysis: *Tom Graesner*, writing—original draft preparation: *Tom Graesner*, writing; review and editing: *Tom Graesner*, *Roland Vogt*; visualization: *Tom Graesner*. All authors have read and agreed to the published version of the manuscript.

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