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# Individual Characteristics as Motivators of Sustainable Behavior in Electronic Vehicle Rental

**Yuchen Wang [1,*], Adeela Gulzari [2] and Victor Prybutok [2]**

[1] Department of Management Science and Information Systems, College of Management, University of Massachusetts Boston, 100 Morrissey Blvd., Boston, MA 02125, USA
[2] Department of Information Technology and Decision Sciences, G. Brint Ryan College of Business, University of North Texas, 1155 Union Circle #311160, Denton, TX 76203, USA; adeelagulzari@my.unt.edu (A.G.); prybutok@unt.edu (V.P.)
* Correspondence: yuchen.wang@umb.edu

**Abstract:** This study investigates the understudied area of motivational factors influencing the rental intention of electric vehicles (EVs) within the context of their integration into urban transportation to combat air pollution and reduce carbon footprints and explores the critical factors influencing consumer behavior towards EV rental, focusing on hedonic motivation, service level, consumer habits, and willingness to pay. Utilizing multiple linear regression analysis on 302 valid samples from Texas, USA, the research identifies the significant impact of these factors on rental intention. Notably, the service level emerges as the most influential predictor while emphasizing the unique and less studied role of hedonic and personal characteristics as essential antecedents of rental intention. The findings, supplemented by a Monte Carlo simulation, reveal that these personal and motivational characteristics are pivotal in shaping rental intentions, accounting for approximately 47.2% of the variance in rental intention. The study contributes valuable insights into the EV rental market, offering theoretical implications for the EV literature and practical strategies for car rental enterprises to tap into consumer patterns effectively.

**Keywords:** electric vehicle; sustainable behavior; rental behavioral model; simulation



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## 1. Introduction

In the modern global landscape, adopting sustainable technology, specifically electric vehicles (EVs), has become of the utmost significance, serving not only as an indicator of technological advancement but also as a central concern in the fight against climate change and ecological accountability [1] (Rigogiannis et al. 2023). Historically reliant on internal combustion engine (ICE) vehicles, the transportation sector has substantially contributed to worldwide greenhouse gas emissions, accounting for approximately 24% of carbon dioxide emissions from fuel combustion worldwide in 2019 [2]. As a result, the transition to EVs is not a fad but rather an essential change in addressing the ongoing global warming and energy crisis. Based on data from the International Energy Agency (IEA), the number of EVs on the road worldwide surpassed 10 million by the end of 2022. This represents a remarkable 48% growth compared to the previous year, despite the worldwide pandemic [3]. The significant increase in the adoption of EVs signifies not only progress in technology and infrastructure readiness but also a change in consumer attitudes towards more environmentally friendly modes of transportation.

This transition to EVs, while laudable, brings forth the imperative of comprehending the perceptions and attitudes of consumers, a factor that heavily influences the rate and nature of EV adoption. Several studies have underscored the importance of consumers' understanding, awareness, and sentiment towards electric mobility. Following this trend, much research and literature not only emphasize the importance of continued technological innovation but also the necessity to address, reshape, and influence public perception and understanding. However, it is rare to investigate consumers' behavior in the EV rental business, and the focus of this research on the personal factors affecting rental intention makes a major contribution to the literature.

In the broader scheme of sustainable development and achieving carbon neutrality, understanding consumer perceptions is not just beneficial but essential. Crafting effective policies, marketing strategies, and educational campaigns that resonate with public sentiments can be the linchpin in fostering faster and more widespread rental EVs. As the world grapples with the repercussions of climate change, integrating technological innovations in transportation with a deep understanding of societal perceptions emerges as a holistic approach to shaping a greener future. This research focuses on the EV rental business in the U.S. Specifically, we study the behavior of consumers who intend to rent EVs for their transportation needs and examine their individual characteristics, such as hedonic concerns and habits. The initial theoretical foundation is the theory of reasoned action [4]. The study further develops the model framework by adding individual personality considerations. In this framework, this research considers willingness to pay, service level, hedonic motivation, and habits as independent variables and evaluates their relationship to the target variable rental intention. In the U.S., rental companies such as Enterprise Rent-A-Car, Hertz, and Turo extend these provisions. The main objective of these enterprises is to provide automobiles for a short period of time, which might range from several hours to an extended span of days or weeks [5]. The concept of leasing, a considerably protracted arrangement often enduring multiple years, and hourly use such as ZIP cars, remain outside the scope of this study. Rental facilities are strategically dispersed across urban locales nationwide, facilitating patrons in accessing and surrendering EVs irrespective of regional constraints [6].

Therefore, the first research question is:

- Are individual characteristics significant in affecting consumers' rental intention of EVs?

By discerning the nexus between individual attributes—ranging from socioeconomic determinants to psychological inclinations—and the propensity to rent EVs, businesses can attain a more granulated understanding of their target audience. Such comprehension would be invaluable for EV rental companies and manufacturers, as it would facilitate the formulation of precision-targeted marketing strategies, tailored leasing packages, and customized outreach campaigns. In an era where market segmentation and personalization are paramount, a rigorous exploration of this research question would empower companies to maximize their return on investment in EV rental, reduce wasted marketing expenditures, and potentially expedite the mainstream adoption of EVs. Moreover, by addressing the nuances of consumer rental behavior in the EV domain, stakeholders can synchronize their business models with the evolving sustainable consumption patterns, thereby reinforcing their competitive positioning and commitment to a greener future. The sample data we acquired facilitate the identification of significant relationships between constructs and enable us to comprehend the triggers that rental organizations can employ to enhance their decision-making processes regarding the establishment of EV rental operations, pricing strategies, and marketing plans. This constitutes a substantial contribution to the existing body of research.

The second research question is:

- If individual characteristics are significant, how do they make an impact on the rental intention?

If individual traits indeed wield a considerable influence on such rental inclinations, understanding the mechanisms behind this interplay has significant business implications. For instance, certain demographic factors, such as age or income level, directly correlated with willingness to pay, might correlate with heightened environmental awareness, subsequently boosting the propensity to rent EVs. Conversely, other factors, such as the service level of the EV infrastructure, might act as deterrents. For businesses, this granularity of insight can be transformative. Recognizing these traits allows firms to tailor their marketing endeavors more astutely, addressing apprehensions and leveraging motivating factors. They can craft specialized campaigns, informed by these insights, to either mitigate barriers or amplify enablers. Such tailored approaches not only optimize resource allocation in marketing and outreach efforts but also facilitate the design of bespoke rental packages, catering to the specificities of diverse consumer segments. Thus, deciphering these individual characteristic dynamics paves the way for more effective business strategies in the burgeoning EV rental market.

In the next segment, we delineate the theoretical underpinnings of our investigation and the associated literature concerning EV rentals. We further illuminate the conceptual framework that steers our inquiry. In Sections 3 and 4, we scrutinize the methodological trajectory of the study and delineate our discoveries, which is then followed by an analytical discourse on our discussion in Section 5. The final segment, Section 6, charts potential avenues for concluding the current research and forthcoming research endeavors.

## 2. Literature Review

### *2.1. Theories and Previous Work*

EV rentals have emerged at the confluence of sustainability goals, technological advancements, and shifting consumer preferences. As this realm of mobility evolves, it becomes essential to qualitatively and quantitatively analyze the impacts, potentials, and challenges associated with EV rentals from the perspective of clean technology.

A pivotal factor driving the integration of EVs into rental markets is the policy landscape, which is one of the motivations of this research. Xue et al. [7] conducted a comprehensive quantitative assessment of the determinants influencing EV policies across 20 countries. Their analysis underscored a strong positive correlation between EV market penetration and the existence of supportive policies, suggesting a potential growth trajectory for EV rentals in regions with robust policy frameworks. Understanding consumer behavior and preferences is imperative to gauge the potential success of EV rentals. Nazari et al. [8] offered a quantitative analysis focused on potential barriers to EV adoption. The study emphasized the significance of a well-established charging infrastructure and the assurance of vehicle range. Their findings indicate that, for the rental market to be receptive to EVs, these two elements need critical attention, as they are pivotal in influencing consumer decisions. Hawkins et al. [9] provided a quantitative life cycle assessment contrasting conventional and EVs. Their findings accentuate the considerably reduced environmental footprint of EVs, particularly when charged with electricity derived from renewable sources. Such environmental benefits solidify the case for integrating EVs into rental fleets as the vanguard of sustainable mobility. While clean technology provides an impetus for EV rentals, economic factors are crucial determinants of their success. Hung et al. [10] delved into the innovative business challenges in the nascent EV sector. Their quantitative discussions illuminated how rental models, given the typically high upfront costs associated with EVs, could serve as a strategic buffer, allowing consumers to experience electric mobility without the commitment of purchase, thus potentially enhancing market penetration.

Distinct hypotheses were used in the publications under the examination of new technology and products like EVs. The authors often amalgamated ideas or isolated individual elements from theories to form their models. Although the TRA (theory of reasoned action) and TPB (theory of planned behavior) have often been used as fundamental theories, as seen by the extensive utilization of attitude and intention constructs, other constructs have been included from theories originating in other disciplines [11]. Initially, the significance of technical advancement theories, including the technology acceptance model (TAM), innovation diffusion theory (IDT), and the unified theory of acceptance and use of technology (UTAUT2), is well-rounded in scrutinizing tech items. From the psychology and social sciences standpoints, the self-determination theory, theory of perceived ownership, construal level theory, and individualism/collectivism dichotomy examine individual characteristics [12].

The literature has centered on the factors affecting the perception of quality towards the purchase of environmentally friendly cars building on the TAM [13], TAM 2 [14,15], TPB [16], and protection motivation theory (PMT) [17]. Several articles have scrutinized rental intention built on the TRA [5]. However, this research is among the first to elucidate the individual characteristics impacting the rental intention based on the TRA in the U.S. Because the TRA, to some extent, considers the features of new technology and products and simultaneously elucidates the personal entities, especially in the context of EVs.

### *2.2. Key Factors Influencing EV Rental*

#### 2.2.1. Hedonic Motivation

Hedonic motivation, as posited in the consumer behavior literature, pertains to the intrinsic pleasure or enjoyment derived from consuming a product or service distinct from its utilitarian function [18]. In the context of EV rentals, hedonic motivation encapsulates the emotive and experiential elements associated with the act of renting and driving an EV. This could encompass the sheer thrill of driving a technologically advanced vehicle, the satisfaction of aligning with eco-friendly choices, or even the prestige of engaging with a novel and innovative mode of transportation. Picot-Coupey et al. [19] argued that hedonic consumption is characterized by the perceived fun or playfulness experienced during the consumption process. Hence, for many consumers, the allure of EV rentals might not solely hinge on pragmatic considerations such as cost savings or environmental benefits; instead, the hedonic pleasures—like the smooth, quiet ride or the futuristic dashboard interfaces—could be pivotal in driving rental intentions. Understanding this hedonic dimension becomes critical for businesses, as it underscores the need to market EVs not just as sustainable transport solutions but also as sources of delightful and enriching experiences [20]. Hence, this research proposes:

**Hypothesis 1 (H1):** *Hedonic motivation has a positive impact on EV rental intentions.*

#### 2.2.2. Willingness to Pay

The concept of willingness to pay encapsulates the inclination of consumers to expend an additional amount [21] for an EV. Due to elevated developmental expenses and sluggish manufacturing rates, consumer goods often bear a steeper price tag during their nascent life cycle phases. Yet, the research by Sahoo et al. [22] ascertained an amplified proclivity among consumers to invest in EVs, a tendency that escalates with an environmentally conscious lifestyle. While the premium pricing of sustainable goods is often perceived as an impediment to their embrace, Przekota [23] posited that consumers gauge price against value rather than strictly as an obstacle. Consequently, when the premium cost of a product is perceived as justifiable, consumers exhibit a readiness [24] to accommodate the elevated price. The assumed relationship between this willingness and the rental intention is:

**Hypothesis 2 (H2):** *Willingness to pay makes a positive impact on EV rental intentions.*

#### 2.2.3. Service Levels

Attaining a lasting competitive edge in the commercial landscape is not merely a function of exceptional products or equitable pricing, irrespective of whether the primary deliverable is tangible or intangible [25]. For a corporation to thrive sustainably, it must consistently offer unparalleled service quality. A pivotal rationale behind this assertion is the inherent difficulty competitors face in emulating service standards compared to replicating product excellence and pricing [26,27]. The service caliber profoundly influences the perceived advantages of an EV and diminishes the psychological burden and additional nonfiscal expenses borne by consumers [28]. Most importantly, as a sustainable high-tech product, rented EVs with well-rounded service levels in charging, tech support, and cruising range checks will boost customers' loyalty. Therefore, the article posits:

**Hypothesis 3 (H3):** *Service levels positively influence EV rental intentions.*

2.2.4. Habits

Consumer habits refer to the recurrent and automated behavioral patterns exhibited by consumers, often entrenched through repeated performance and typically triggered by situational cues [29]. These habitual behaviors, once formed, are resistant to change and can significantly influence purchase and consumption decisions, often bypassing deliberative cognitive processes. In the realm of EV rentals, consumer habits can manifest in multiple ways. For instance, an individual accustomed to renting gasoline-powered cars during travel might instinctively choose the same option, even if EVs offer superior benefits, simply due to the inertia of their established habits. Conversely, someone who has consistently experienced the advantages of EVs might habitually opt for them, underscoring the rental behaviors anchored in past repetitious actions. Degirmenci and Recker [30] contended that breaking old habits and fostering new ones necessitates disruptions in the environment or routine. Thus, businesses in the EV rental sector, aiming to shift entrenched consumer habits, need to introduce interventions or cues that disrupt habitual pathways and encourage the conscious reconsideration of rental choices. Hypothesis 4 below is to test this statement:

**Hypothesis 4 (H4):** *Habits positively influence EV rental intentions.*

## 3. Materials and Methods

This research was orchestrated and executed as a sectional survey in a bifurcated manner. Initially, a preliminary study was undertaken, garnering insights from a scholar renowned for survey research publications and credited with quality engineering qualifications. Furthermore, input was obtained from 15 doctoral candidates spanning fields like engineering, logistics, chemistry, and information technology, all proficient in survey investigations. Subsequently, in 2021, data acquisition occurred at a scholarly establishment located in Texas, U.S., by randomly selecting volunteers using the Qualtrics survey tool. Because location is typically considered a priority for rental business [31], this article captured the unique position of Texas in the evolving landscape of EV usage. In the past 5 years, Texas has experienced a significant uptick in EV adoption, albeit at a pace somewhat slower than states like California, which leads the nation in EV usage. Rental companies in Texas, such as Enterprise and Hertz, have been steadily increasing their fleets of electric vehicles to meet the growing demand. Texas has over 1800 public charging station locations [32]. The distribution of electric vehicle (EV) rentals in Texas is primarily centered in its major metropolitan regions. For instance, UFODrive, which specializes exclusively in electric car rentals, exemplifies this with its establishment in Austin's urban core at 510 Guadalupe Street. This reflects a broader trend of EV rental services favoring urbanized areas, where advanced infrastructure such as charging stations is more prevalent [1] and the higher demand is driven by larger populations and increased tourism. This urban-centric pattern in EV rental service allocation is also observed in other states, where companies typically focus on large cities [17].

A thorough study was conducted to investigate the elements that influence people's intentions to rent an EV. A poll was designed to include a wide range of people from different demographic backgrounds. In order to guarantee the dependability and significance of the data, rigorous filtering criteria were used. Initially, replies that took more than seven minutes to complete were chosen, since this suggested that the respondents spent more time thinking and considering the survey questions in a careful and comprehensive manner (see Appendix A Table A2). The purpose of setting these criteria was to improve the quality of the data by removing superficial and potentially less trustworthy replies.

In addition, the dataset was refined to include only those respondents who explicitly indicated an intention to rent EVs. The selection criteria played a crucial role in ensuring that the dataset only included individuals from the target population who were prospective electric vehicle renters. This increased the relevance of the results specifically to this group.

The main purpose of these carefully selected statistics was to analyze the many individual traits that can influence someone's preference for renting an electric vehicle. The research sought to use statistical analysis methods on this filtered dataset to identify the main factors that determine EV rental intention and measure the magnitude of their impact. This technique enables players in the EV rental business to gain detailed knowledge of the complex dynamics involved. This information is crucial for them to develop successful strategies and meet the changing demands of their prospective customers. Out of the 836 acquired responses, a fraction was excluded after applying the filter, and 302 entries persisted. The ethnographic composition of this sample mirrors the racial delineations observed in the 2020 U.S. Census data (see Appendix A Table A1). The analysis was conducted using SmartPLS 4.0 and JMP in a university workstation, and the configuration was an Intel Core i7 (tenth generation) with 32 GB RAM.

### *3.1. Consistency and Validity*

In the principal component analysis, every item loading surpassed the 0.75 threshold. The metrics for each constituent factor underwent an evaluation for internal congruence and were subsequently subjected to a confirmatory factor analysis [33]. The calculated Cronbach's alpha values for the factors, habits, hedonic motivation, service level, and willingness to pay stood at 0.88, 0.85, 0.91, and 0.90, respectively. Consequently, each of these Cronbach's alpha values exceeded the 0.8 benchmark, signifying internal consistency [34]. The construct validity represented by the individual metrics was probed through examination of the construct reliability (CR). Convergent validity (CV) embodies the degree to which theoretically associated metrics interrelate and encapsulate a unified construct. A CR value equal to or surpassing 0.7 was deemed satisfactory [35], signifying the presence of convergent validity. Furthermore, all composite reliability coefficients surpassed 0.74. The variance inflation factor (VIF) was 0.94, thereby suggesting an absence of multicollinearity amidst the predictor variables.

### *3.2. Methods*

The construction of a multiple linear regression model in this research aims to elucidate the determinants of EV rental intention. In this model, EV rental intention is posited as the dependent variable, reflecting the likelihood or propensity of individuals to rent an EV. The independent variables lean on individual characteristics only. Thus, we can get

$$EV\ Rental\ Intention_i = \beta_0 + \beta_1 Habit_i + \beta_2 Hedonic_i + \beta_3 Services_i + \beta_4 PayWills_i + \varepsilon_i \quad (1)$$

where $i$ is from 1 to 302 for the observations and $\beta$s are the coefficients, and $\varepsilon_i$ is the error term.

To control the potential confounding effects, demographics such as age, gender identity, educational attainment, race, household economic status, and parental socio-professional classification are included as control variables. The regression coefficients obtained from this model will indicate the direction and magnitude of the relationship between each independent variable and EV rental intention, offering insights into which factors are most salient in determining the likelihood of renting an EV. This model, therefore, serves as a robust analytical tool to guide stakeholders in the EV rental industry in understanding customer behavior and tailoring their services accordingly.

## 4. Results

Utilizing the ordinary least squares (OLS) method [36], this research delineates the multiple linear regression analysis results (Table 1), examining the relationship between rental intention and four independent predictors. The results are itemized into unstandardized coefficients, standardized coefficients, $t$-values, and $p$-values. These unstandardized coefficients elucidate the absolute change in the dependent variable for a one-unit shift in the predictor, with other predictors held constant. For example, a unitary rise in the service level and willingness to pay augments rental intentions by 0.24 and 0.154 units, respectively, when other predictors are invariant. These standardized coefficients represent the number of standard deviations the dependent variable will change due to a one standard deviation alteration in the predictor. It provides a scale-free metric enabling the comparison of the relative strengths of predictors. In this analysis, the service level (β = 0.303) stands out as the most influential predictor relative to the others in affecting rental intention.

**Table 1.** Regression results with 4 predictors.

| Variables | Unstandardized Coefficients | Standardized Coefficients | *t*-Value | *p*-Value |
|---|---|---|---|---|
| Habits | 0.165 | 0.233 | 3.616 | 0.000 |
| Hedonic Motivation | 0.192 | 0.251 | 3.926 | 0.000 |
| Service Levels | 0.24 | 0.303 | 4.951 | 0.000 |
| Willingness to Pay | 0.154 | 0.259 | 4.138 | 0.000 |
| Intercept | 0.985 | 0 | 4.17 | 0.000 |
| R-Square | | 0.472 | | |
| Adjusted R-square | | 0.459 | | |
| Durbin Watson test | | 1.935 | | |

*t*-values offer insights into the number of standard deviations away the observed coefficient values are from zero in the sample distribution. A large absolute *t*-value suggests a higher likelihood that the relationship between the predictor and the dependent variable is not due to chance. All predictors in Table 1 manifest significant *t*-values, underscoring their meaningful association with rental intention. *p*-values are indicative of the statistical significance of the predictors. Conventionally, a *p*-value less than 0.01 is deemed significant for this research. Here, all *p*-values are 0.000, affirming the statistical significance of each predictor in explaining the variance in rental intention.

R-square intimates that approximately 47.2% of the variance in rental intention can be elucidated by the collective variance in the independent variables. This suggests a moderate explanatory power of the model, indicating that almost half of the shifts in rental intention are accounted for by the predictors under scrutiny. A higher R-square does not necessarily connote a better model. It merely portrays the proportion of variability explained. An enhancement over the rudimentary R-square, the adjusted R-square accounts for the number of predictors in the model. It offers a more accurate portrayal of the model's explanatory prowess, especially crucial in multiple regression analyses where the mere addition of variables can inflate the R-square. A value of 45.9% indicates that, after adjusting for the number of predictors, the model elucidates approximately 45.9% of the variability in rental intention.

The Durbin–Watson test ascertains the presence of autocorrelation (a sequence of correlation patterns) in the residuals from a regression analysis. Typically, values ranging between 1.5 and 2.5 are deemed acceptable, indicating the absence of significant autocorrelation [37]. The value of 1.935 sits comfortably within this range, suggesting the residuals are essentially random and devoid of any discernible patterns.

All the hypotheses (H1 to H4) are extremely significant, with the *p*-values being close to zero, indicating that the alternative hypotheses are accepted.

Table 2 closely scrutinizes the personal entities. For clarity and comparison, the results are also structured into unstandardized coefficients, standardized coefficients, *t*-values, and *p*-values. An increment by one unit in habits is tantamount to an enhancement of 0.227 units in rental intention, with other variables held constant, and it is 0.265 for hedonic motivation. And with hedonic motivation registering a β of 0.347 and habits posting a β of 0.321, both factors are almost equivalently influential in determining rental intention, with hedonic motivation holding a slight edge.

**Table 2.** Regression results with 2 predictors.

| Variables | Unstandardized Coefficients | Standardized Coefficients | *t*-Value | *p*-Value |
|---|---|---|---|---|
| Hedonic Motivation | 0.265 | 0.347 | 4.87 | 0.000 |
| Habits | 0.227 | 0.321 | 4.507 | 0.000 |
| Intercept | 1.893 | 0 | 8.666 | 0.000 |
| R-Square | | 0.302 | | |
| Adjusted R-square | | 0.293 | | |
| Durbin Watson test | | 1.776 | | |

Both predictors exhibit pronounced *t*-values, indicating their substantial association with rental intention is unlikely to be by chance. Reinforcing the significance of the predictors, the *p*-values stand at 0.000, well below the conventional threshold of 0.01. This reaffirms the statistical significance of both predictors in elucidating the variability in rental intention.

Hedonic motivation embodies the intrinsic pleasure or emotional satisfaction derived from renting. Its prominent coefficient accentuates elements that amplify pleasure or emotional gratification—be it through luxury features, add-on services, or experiential offerings—that can act as a potent lever to elevate rental intention. Habitual behaviors, as patterns that consumers recurrently exhibit, underscore the importance of loyalty programs, customer retention strategies, and consistent service delivery. Recognizing and rewarding recurring customers can fortify their habitual inclinations, thereby buttressing rental intentions.

In Table 2, the R-square value of 0.302 denotes that approximately 30.2% of the variability in rental intention can be attributed to the combined effects of habits and hedonic motivation. In this case, the adjusted R-square value of 0.293 suggests that, after adjusting for the number of predictors, roughly 29.3% of the variance in rental intention can be explained. The value of 1.776 from the Durbin–Watson test in this context suggests that the residuals are free from autocorrelation, and an extremely small *p*-value (under the 0.00001 significant level) indicates that the two-variable personal entity model is significant.

## 5. Discussion

### *5.1. Theoretical Contribution*

Consumers make choices based on their preferences and the utility they derive from goods and services, which directly influences their willingness to pay for those products or services. This study evaluates the effect of consumer's habits, hedonic motivation, satisfaction with the service level, and willingness to pay on the consumer's intention to rent an EV. The predictor habit has a positive impact on the EV rental intention. This finding implies that individuals engage in behavior as a result of acquired knowledge and skills over time. Our result is consistent with prior research that has indicated that habitual tendencies directly influence the intention to engage in specific behaviors, highlighting their crucial role as a determinant in forecasting the adoption of technology [26]. Similarly, hedonic motivation has a positive relationship with EV rental intention. Several studies have substantiated the direct influence of hedonic motivation on customers' preferences to adopt a novel technology [26,38]. In this study, we tested and found a positive relationship for hedonic motivation within the context of renting an EV. The predictors' service level and willingness to pay positively impacted the rental intention of EVs, which is consistent with the findings from prior studies in the EV literature [5,39].

From the regression analysis, when considering four predictors: habits, hedonic motivation, service level, and willingness to pay, the R-square was 47.2%, and the adjusted R-square was 45.9%, which were substantially higher than the 30.2% and 29.3% explained by the model with just two predictors. However, the R-square will always increase when predictors are added, since the regression error is lower [40]. In this case, the R-square dropped by 17%, but the adjusted R-square decreased by 16.6%. Both of the models were able to provide significant insights with various focuses.

This research also conducted a Monte Carlo simulation on the model to understand the overall distribution and trend of the rental intention. The desirability function (Figure 1) assigns a numerical value to outcomes based on how closely they meet a particular goal or objective. In scenarios where there are multiple outcomes to consider in this research, and these outcomes may have conflicting requirements, desirability functions become very useful. This is because they allow for combining and balancing these outcomes in a standardized way. The rental intention has four attributes to consider. Figure 2 adjusts the hedonic motivation, willingness to pay, and service level to be as high as possible, while the construct habits has a wider range, indicating the resilience of this regressor. The habits variable needs extra weight to push the rental intention to the upper boundary. The desirability of this paper provides a structured way to navigate and optimize complex situations with multiple, potentially conflicting objectives. Notably, EV rental users present a distinct array of difficulties, predominantly attributable to the fleeting nature of rental exchanges and the heterogeneous demographic composition. Survey data collection can be challenging due to the transient and frequently irregular utilization patterns exhibited by these vehicles. Moreover, the demographics of rental EV users are diverse, including those who are acquainted with technology, socioeconomic standing, and age, which further complicates the standardization of survey methodologies. Utilizing a Monte Carlo simulation offers significant value in this particular context. Researchers have the ability to simulate an extensive range of potential outcomes. The green distributions in Figures 1 and 2 deduce patterns, detect possible anomalies, and provide a more holistic understanding of the attitudes and inclinations of rental EV users by depicting that the adoption of rental EVs is still not extremely strong but somehow increased. As a result, the curve is a leptokurtic distribution with high kurtosis, indicating people want to give rental EVs a try but are not fully committed.

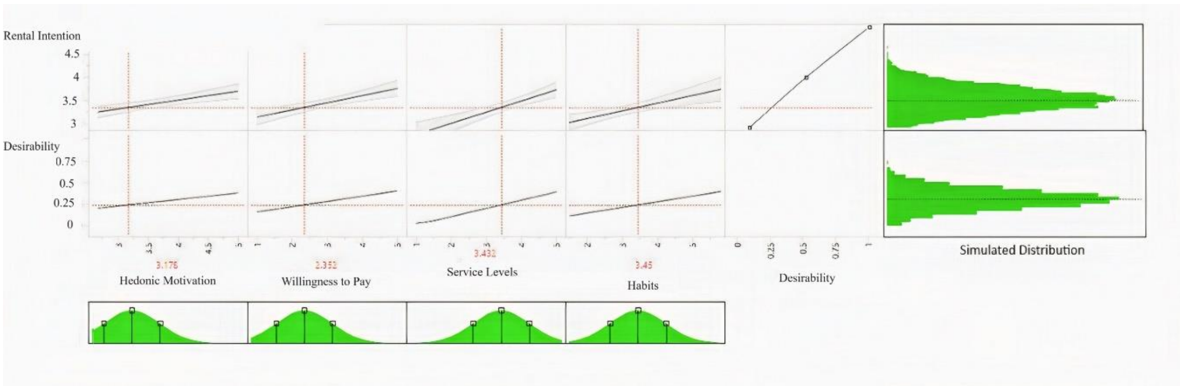


**Figure 1.** Simulation of the 4-regressor model.

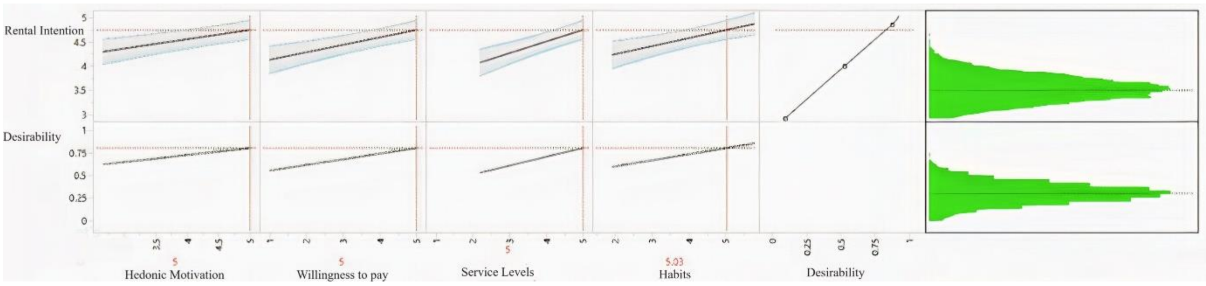


**Figure 2.** Simulation of the 4-regressor model after the adjustment on desirability.

This research primarily utilizes simulations as a tool for extending observations and insights rather than as the main result. The inclusion of these simulations is intended to directly link these extended observations to the practical implications they hold for businesses and manufacturers. This approach is designed to provide a seamless integration of theoretical findings with applied insights, which we believe enhances the value of our research.

### *5.2. Practical Implementation*

Gaining insight into the impact of motivational variables, including habitual patterns and hedonic motivation, on consumer behavior regarding the adoption of EVs is of paramount significance. EVs predominantly operate within urban settings. Their subdued noise, rapid acceleration, and seamless deceleration contribute to an enhanced driving experience for the operator. This distinctive driving pleasure contrasts with that of an ICE, potentially serving as a psychological determinant influencing the driver's acceptance.

This comparative analysis underscores the significant influence that the service level and willingness to pay have on rental intentions. From a business perspective, while habits and hedonic motivation are undoubtedly important, neglecting the factors of service level and willingness to pay might render businesses vulnerable to overlooking crucial determinants that could greatly impact rental intentions. To holistically understand customer behaviors and shape effective business strategies, it is imperative to factor in all these elements; companies in the rental domain might need to invest in enhancing service levels and understanding the pricing elasticity of their customers. While cultivating habits and catering to hedonic motivations are crucial, these alone might not be sufficient to drive rental intentions, as evidenced by the comparative R-square values.

This study was conducted in a large metropolitan area in Texas. The area from which the sample originated has advantages, because it has a greater diversity than many areas in the U.S. because of the large migration to the metroplex as a result of new employment opportunities. However, it also suggests that the findings are more limited to a large metropolitan area with a moderate climate in terms of vehicle utility. While the results are important because they are likely relevant to many large metropolitan areas, we do not anticipate the findings would transfer to remote areas or areas with harsh terrain.

By considering all these elements, businesses can make more informed decisions, optimize their offerings, and strategically position themselves in the market. Empirical studies have established that individuals with prior exposure to EVs exhibit a heightened inclination toward their acquisition and utilization. The model with two regressors implies that both the habitual behaviors of customers and their pursuit of pleasure or satisfaction in renting significantly impact their rental intention. Organizations can leverage this insight to bolster their marketing and engagement strategies, aligning them more closely with consumer behavior and preferences.

## 6. Conclusions

The integration of EVs in urban transportation, aimed at curbing air pollution and reducing the carbon footprint, has emerged as a compelling research domain. However, the motivational factors influencing the rental intention of EVs remain inadequately explored in the existing literature. To address this gap in the literature, the present study characterizes the motivational factors behind the rental intention of EVs, including consumers' habits, hedonic motivation, satisfaction with the service level, and willingness to pay. A multiple linear regression analysis was conducted to explore the association between rental intention and the four independent predictors, and 302 valid samples were collected in the southern region of the U.S. Additionally, this study employed a Monte Carlo simulation to gain insights into the overall distribution and trajectory of the rental intention model.

The main statistical findings indicate that the theoretical model exhibits good explanatory capabilities and predictive validity, with an R-Square of 47.2%. All $p$-values recorded as 0.000 affirm the statistical significance of each predictor in explaining the variability observed in rental intention, indicating that the predictors are important antecedents of rental intention. Habits and hedonic motivation can significantly influence purchase and consumption decisions, often bypassing deliberative cognitive processes. Consumers who prioritize price considerations will engage in EV rental only when they perceive value and demonstrate a willingness to pay a premium. The quality of service significantly shapes the perceived benefits of an EV while concurrently reducing the psychological burden and additional nonmonetary expenses incurred by consumers. The investigation of individual characteristics and their impact on rental preferences holds substantial business implications. Based on the significant hypotheses on individual characteristics, car rental enterprises would benefit from an exploration of abstract motivational factors to enhance the consumer experience with EV rentals. Car rental enterprises need to implement a series of innovative strategies, such as enhancing EV accessibility and providing consumers with electronic maps of charging stations and additional service resources, to enhance the overall experience of EV rentals.

Some limitations of this study warrant acknowledgment, which calls for future research and alternative methodological approaches. The data collected for this study were cross-sectional, which, although widely employed in the EV literature, can provide limited insights into the behavioral intentions of consumers. Longitudinal studies, while more resource-intensive compared to cross-sectional studies, yield more robust evidence for behavioral models. This study centers on consumer rental behavior within the U.S. market, particularly considering the context of higher rental costs for EVs compared to gasoline-powered cars.

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**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

**Data Availability Statement:** Private data are available upon request.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## Appendix A

**Table A1.** Demographics of the sample data.

| Demographics | Categories | Percentage |
|---|---|---|
| Age | $18 \leq$ Early Adults $\leq 21$ | 49% |
| | 22-25 years old | 41% |
| | Adult $\geq 26$ years old | 10% |
| Gender Identity | Females | 52% |
| | Male | 47% |
| | Other | 1% |
| Educational Attainment | Undergraduates | 90% |
| | Graduate and doctoral students | 9% |
| | Other | 1% |

**Table A1.** *Cont.*

| Demographics | Categories | Percentage |
|---|---|---|
| Race | African American<br>Mixed<br>Asian<br>Caucasian | 10%<br>24%<br>17%<br>49% |
| Household Economic Status | Over 150,000 USD<br>100,000 to 149,999 USD<br>50,000 to 99,999 USD<br>Less than 49,000 USD | 15%<br>21%<br>38%<br>26% |
| Parental Socio-Professional Classification | Managerial and Professional Positions<br>Nonprofessional Positions | 60%<br>40% |

**Table A2.** Survey instrument items.

| Construct | Items (Short Form) | Sources |
|---|---|---|
| Hedonic Motivation | I find using an electric vehicle to be enjoyable.<br>In my opinion, using an electric car is a pleasurable experience.<br>In my opinion, operating an electric car is quite enjoyable.<br>An electric car offers several exciting features and functionalities.<br>Operating an electric car provides a sensation akin to playing a game. | [41] |
| Willingness to Pay | The rent prices of electric vehicles are unacceptably high<br>As soon as a new model of car becomes available in a car rental company, I need to rent it<br>For a great car I would accept a higher rental price<br>For a green technology I would accept a higher price | [42] |
| Habits | I have developed a routine of driving an electric vehicle.<br>I need to drive an electric automobile.<br>When confronted with driving responsibilities, opting for the rental electric vehicles is a clear and logical decision for me.<br>I possess expertise in operating a hybrid vehicle.<br>I am capable of altering my practice of operating a vehicle powered by gasoline. | [26] |
| Service Level | The customer care department will address any issue I have with the rental vehicle.<br>If I am dissatisfied with the rental vehicle, I can promptly lodge a complaint with the car rental operator. If I am dissatisfied, I have the option to lodge a complaint.<br>The customer service personnel of electric car rental firms are accommodating and supportive.The customer support department for electric car rentals offers sufficient assistance. | [43] |
| Rental intention | In the foreseeable future, I plan to frequently lease battery-electric automobiles.<br>Probability of leasing an electric vehicle for my next vacation.<br>Seeking to rent an electric car for my transportation needs.<br>Preferential inclination towards renting an electric car as opposed to a fuel-powered vehicle. | [44] |

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