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Personal and technological determinants of electric vehicle adoption in Oman: The moderating role of government innovation capability

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ABSTRACT

The adoption of electric vehicles (EVs) is a crucial step toward sustainable transportation, yet its expansion in emerging markets like Oman faces several challenges. Limited charging infrastructure, technological readiness, and policy support impact the adoption rate. This study investigates the interplay between personal and technological determinants influencing EV adoption in Oman, emphasizing the moderating role of government innovation capability. A structured survey was conducted among 410 decision-makers from key regulatory bodies, and data were analysed using structural equation modelling. The research confirms that social norms, together with perceived usefulness and driver IT competency and system quality, substantially boost EV adoption, but insufficient charging facilities continue as the primary impediment. The capability for government innovation acts as a moderator that alters how social norms, system quality, and charging infrastructure influence the adoption of EVs. The study shows that EV adoption requires both governmental policy intervention and infrastructure development and consumer education programs for successful implementation. This research connects government innovation capability to established models, guiding both policymakers and industry leaders who want to develop a technologically progressive EV ecosystem. Research should expand beyond this study by using multiple stakeholder perspectives and combining longitudinal timeframes and various research methods to achieve better insights into electric vehicle adoption patterns.

Keywords: Social Norms, Perceived Usefulness, IT Competencies, System Quality, Lack of charging infrastructure, Electric Vehicles, Government Innovation Capability, Perceived Value, Oman.

1. Introduction

Global sustainability in transportation depends heavily on the adoption of electric vehicles (EVs). Oman's rising market status creates distinct pathways and technical hurdles in implementing EV technology. Rising environmental knowledge and modern technology development have together modified how consumers view electric vehicles. The adoption of electric vehicles remains limited because of poor charging infrastructure alongside expensive initial EV purchase costs. Multiple strategic actions must be implemented to address these current obstacles, including government policies, investments in charging networks, and regulatory frameworks that support EV adoption [1-2].

The worldwide adoption of electric vehicles relies primarily on policies developed to achieve sustainability and cut carbon emissions. Limited research exists about EV adoption incentives implemented by developed economies compared to the underdeveloped understanding of Middle Eastern markets [3]. The assessment of factors driving EV adoption in Oman serves crucial purposes for fixing market problems and establishing effective regulatory frameworks. The research aims to address the knowledge gap by analyzing personal and technological influences on EV adoption alongside an investigation of government innovation capability as a moderating factor.

The implementation of government policies stands as a crucial factor in addressing EV adoption obstacles by dealing with the indirect network effect caused by inadequate charging stations, which scare consumers away, and low demand that hinders investments [4]. The implementation of tax credits, as well as subsidies and fuel policy reforms by government entities, makes EVs more financially appealing to consumers [5]. A sustainable transportation system requires an expansion of charging infrastructure that comes from public-private partnerships and targeted incentives to reduce uncertainty [6].
The strategic implementation of EVs in Oman represents progress toward sustainable transportation systems while affordability issues, infrastructure gaps, and awareness problems remain. The Omani context lacks sufficient analysis of how government innovation capability influences this energy transition, according to [7]. This research addresses this knowledge gap by combining government innovation elements into adoption models while providing a policy-specific framework that differs from previous approaches that focused on consumers or technology [8]. The research evaluates how this mechanism operates to deliver practical guidance to policymakers who seek to drive EV adoption through strategic interventions [9].

2. Key determinants of electric vehicle adoption

Different individual elements, together with technological requirements and infrastructure components, determine the adoption of electric vehicles (EVs). Consumer behavior regarding EV adoption is significantly influenced by social norms, which can either support or prevent the adoption process. Research shows that purchasing decisions are primarily determined by how consumers perceive value, their personal beliefs, and how others perceive them [8]. Social norms demonstrate different strengths depending on the specific context, which requires localized investigations, especially in Oman. The recognition of useful benefits regarding cost savings coupled with environmental sustainability among consumers drives their adoption of EVs [14-17]. Studies about the effects of perceived usefulness on EV adoption are extensive, but specific investigations linking this factor to government innovation capabilities remain scarce.

Personal IT competency serves as a critical factor because it determines a consumer's capability to use digital interfaces found in electric vehicles. Research findings indicate that IT competency makes adoption easier [18], but other studies show that it lacks significance when applied to different technological settings [19]. Research needs to study the impact of IT competency on EV adoption in Oman due to rising EV digitalization. The adoption decisions of customers heavily depend on system quality aspects such as battery performance, charging speed, and software reliability. The literature demonstrates that system quality determines how consumers trust digital and transport technologies [21-22]. The impact of system quality on EV adoption in Oman's regulatory framework and infrastructural environment has not been thoroughly investigated.

A major barrier to EV adoption is the limited charging infrastructure, which directly impacts consumer confidence [23–24]. In Oman, this scarcity leads to range anxiety, reducing the attractiveness of EV ownership. While other countries have responded with infrastructure investments, Oman's approach remains under-researched. Perceived value also influences adoption, as consumers weigh cost savings, sustainability, and technological benefits [25–26]. It is known to mediate the effects of system quality and social norms on adoption [27], yet its role in Oman's EV landscape is still unclear. Additionally, the indirect network effect, where low adoption discourages infrastructure investment and vice versa, poses a challenge [6]. Addressing this requires coordinated policy efforts, including public-private partnerships, fuel subsidy reforms, and tax incentives to enhance EV affordability [5].

EV adoption depends heavily on government innovation capabilities because these capabilities establish policies while determining investment strategies and setting regulatory rules. The adoption of new technologies in fields like fintech [29], smart agriculture [30], and healthcare [31] benefits from robust institutional backing, which creates fewer barriers through incentive programs, streamlined regulations, and new infrastructure development. Research has yet to establish the extent to which government innovation capability influences EV adoption in Oman. System quality and infrastructure challenges can be improved through government intervention, as shown by research [32], but separate adoption factors include IT competency and perceived usefulness. Figure 1 shows the study framework that links these determinants with government innovation capability to analyze the direct and moderated effects on EV adoption in Oman.

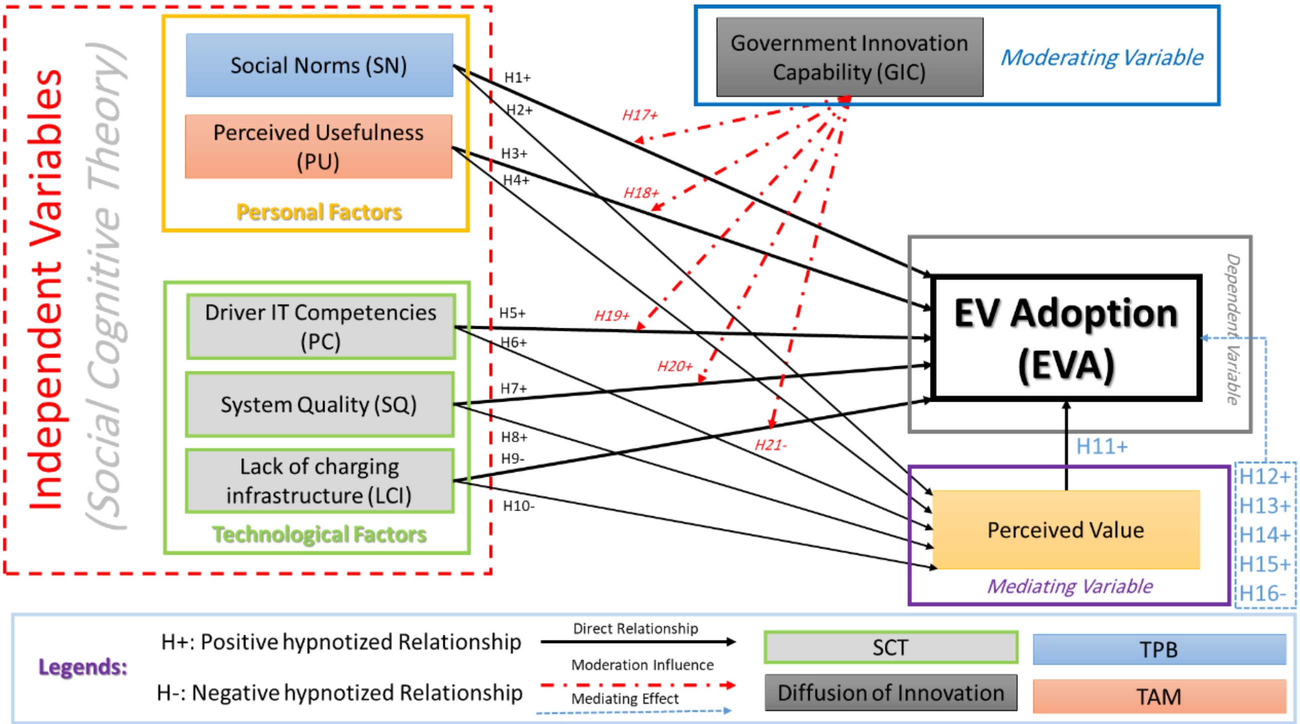

Figure 1. Research Framework

3. Methodology

This research adopts structural equation modeling (SEM) to analyze determinants of electric vehicle (EV) adoption in Oman through a quantitative research methodology. The research included a structured survey involving 410 decision-makers from Oman's EV regulatory bodies, while data processing was conducted through SPSS and Smart PLS for assessing measurement and structural models. The research framework includes government innovation capability as a moderating factor that enables a detailed policy analysis of EV adoption influences.

To achieve an impartial selection of participants, the study employed a simple random sampling technique. The researchers utilized statistical software to create a random employee list obtained from major regulatory and policymaking entities in Oman. The method provided all participants with equal selection chances to reduce potential bias in the process. The target population included staff from the Ministry of Commerce and Industry, Ministry of Transport, Communications, and Information Technology, Environment Authority, Authority for Public Services Regulation, and the ROP Traffic Department, all institutions central to EV policymaking and whose employees are financially positioned to consider EV ownership. Participants spanned various organizational levels, from department heads to middle and top management, providing a broad perspective on EV adoption. A total of 410 questionnaires were distributed, with voluntary participation, confidentiality assured, and study findings available upon request. This approach ensured a diverse, representative sample and enhanced the reliability of the study's findings.

The study utilized a structured questionnaire comprising 35 items measured on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Measurement items were adapted from validated instruments used in prior research, as detailed in Table 1. To ensure credibility and validity, a pilot study was conducted with 30 participants from the target organizations, assessing clarity, reliability, and construct validity. Based on feedback, minor modifications were made for better comprehensibility. Cronbach's alpha values for all constructs exceeded 0.7, confirming reliability.

Data analysis was performed using Smart PLS 4, a variance-based structural equation modeling (SEM) technique. Smart PLS was chosen over AMOS due to its suitability for moderate sample sizes, ability to handle complex moderation and mediation effects, and flexibility in analyzing non-normally distributed data. Additionally, its predictive-oriented approach was well-suited for assessing policy-driven impacts on EV adoption.

The questionnaire was designed to align with the study's objectives, ensuring that measurement items accurately captured the investigated variables. Validated research instruments from previous studies enhanced the study methodology by creating a solid structure for analyzing EV adoption influenced by government policies.

Table 1. Questionnaire Development

Variable	No. of Items	Reference
Social Norms	4	[33]
Perceived Usefulness	4	[34]
Personal IT Competencies	4	[35]
System Quality	4	[36]
Lack of Charging Infrastructure	4	[37-38]
Perceived Value	4	[39]
Government Innovation Capability	5	[40]
EVs Adoption	6	[41]

4. Results and discussion

The current study has assessed the proposed model in two steps, namely, the assessment of the measurement model (outer model) and the assessment of the structural model (inner model). However, prior to these two steps, a brief explanation is given regarding the respondents' profiles.

In the demographic information section, respondents were categorized by their Gender, Age, Level of employment, and Education, as displayed in Table 2.

Table 2. Questionnaire Development

Item	Option	Frequency	Percent
Gender	Male	251	61.20
	Female	159	38.80
Age	20-25 years	102	24.90
	26-35 years	178	43.40
	36-45 years	85	20.70
	46-55 years	35	8.50
	56 years and above	10	2.40
Employment	First level Employee	108	26.30
	Head of department	82	20.00
	Middle management	100	24.40
	Head of division	60	14.60
	Top management	60	14.60
Education	University degree	228	55.60
	Master	133	32.40
	PhD	49	11.90

The research model was assessed using Smart PLS 4, incorporating both measurement model analysis to evaluate validity and reliability and structural model analysis to test the hypothesized relationships. During the initial analysis, one item (GIC2) exhibited a low factor loading of 0.058, falling below the acceptable threshold recommended by [42]. To enhance the robustness of the measurement model, GIC2 was removed in the second iteration, ensuring that all remaining items met the required factor loading criteria. Following this modification, all constructs successfully achieved the recommended cutoff values for Factor Loadings, Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE), confirming the model's validity and reliability. The final results are summarized in Table 3 and Figure 2.

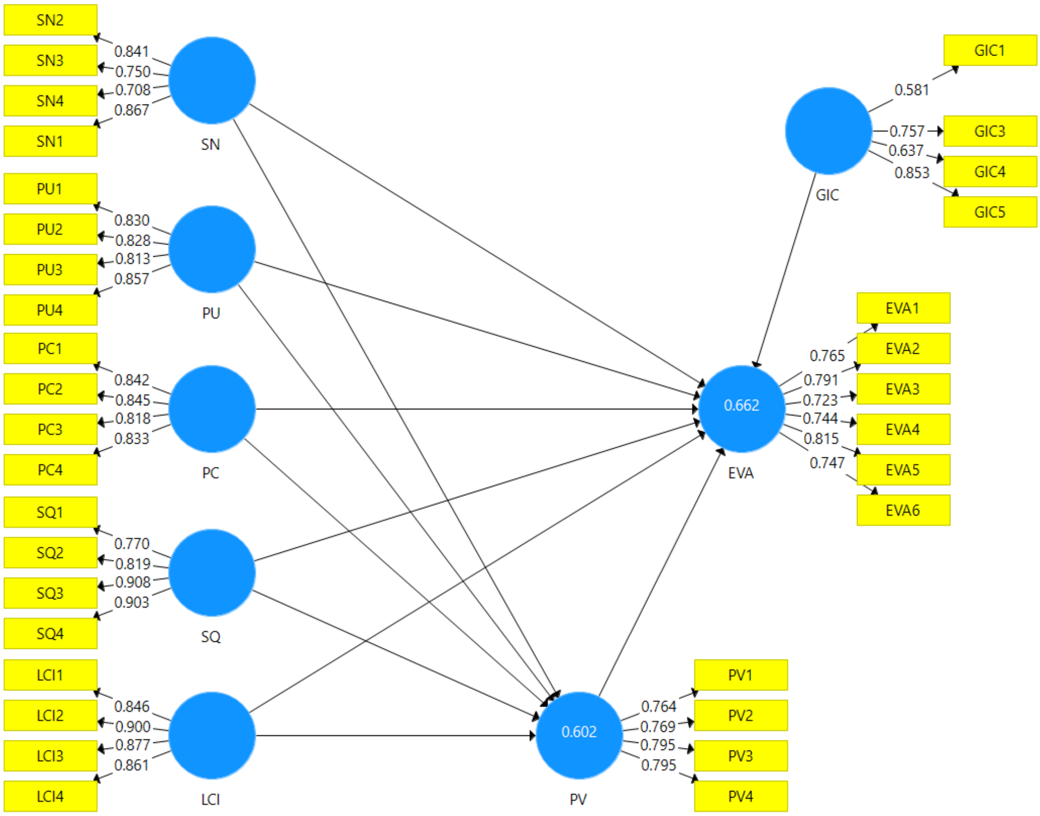

Figure 2. PLS Algorithm results

Table 3. Convergent validity

Variables	Items	Factor Loadings	Cronbach's Alpha	CR	AVE
EV Adoption	EVA1	0.765	0.858	0.894	0.585
	EVA2	0.791			
	EVA3	0.723			
	EVA4	0.744			
	EVA5	0.815			
	EVA6	0.747			
Government Innovation Capability	GIC1	0.581	0.735	0.803	0.511
	GIC3	0.757			
	GIC4	0.637			
	GIC5	0.853			
Lack of Charging infrastructure	LCI1	0.846	0.894	0.927	0.759
	LCI2	0.900			
	LCI3	0.877			
	LCI4	0.861			
Personal IT Competencies	PC1	0.842	0.855	0.902	0.697
	PC2	0.845			
	PC3	0.818			
	PC4	0.833			
Perceived Usefulness	PU1	0.830	0.853	0.900	0.692
	PU2	0.828			
	PU3	0.813			
	PU4	0.857			
Perceived Value	PV1	0.764	0.787	0.862	0.610
	PV2	0.769			

Variables	Items	Factor Loadings	Cronbach's Alpha	CR	AVE
	PV3	0.795			
	PV4	0.795			
Social Norms	SN1	0.867	0.807	0.871	0.630
	SN2	0.841			
	SN3	0.750			
	SN4	0.708			
System Quality	SQ1	0.770	0.872	0.914	0.726
	SQ2	0.819			
	SQ3	0.908			
	SQ4	0.903			

Next, discriminant validity was assessed to determine the extent to which each construct is truly distinct from the others. To evaluate distinguishing validity, correlations between variables were analyzed. The model estimation did not exceed 0.95, aligning with the recommended threshold suggested by [43]. Validity was further examined using the Fornell and Larcker criterion, which compares the correlations between constructs with the square root of the average variance extracted (AVE) for each construct [43], [44]. As shown in Table 4, all values remained below the recommended cutoff of 0.90, confirming that the constructs maintain adequate discriminant validity [44].

Table 4. Discriminant validity - Fornell and Larcker Criterion

	EVA	GIC	LCI	PC	PU	PV	SN	SQ
EVA	0.765							
GIC	0.04	0.715						
LCI	0.639	0.077	0.871					
PC	0.672	0.049	0.618	0.835				
PU	0.685	0.01	0.644	0.683	0.832			
PV	0.742	0.11	0.589	0.663	0.672	0.781		
SN	0.187	0.033	0.169	0.088	0.118	0.095	0.794	
SQ	0.672	0.038	0.561	0.75	0.682	0.721	0.076	0.852

Additionally, the Heterotrait-Monotrait ratio (HTMT) was assessed to estimate the true correlation between constructs if they were measured without error, ensuring their reliability. The HTMT represents the mean of all correlations between indicators measuring different constructs (Heterotrait-Monotrait correlations) relative to the geometric mean of the correlations between indicators measuring the same construct. This method is widely used for the assessment of discriminant validity [42]. According to recommendations from the literature, an HTMT value below 0.90 indicates acceptable discriminant validity [45]. As shown in Table 5, all values met this criterion, confirming the distinctiveness of the constructs.

Table 5. Discriminant validity - HTMT

	EVA	GIC	LCI	PC	PU	PV	SN
EVA							
GIC	0.089						
LCI	0.731	0.090					
PC	0.779	0.064	0.705				
PU	0.789	0.061	0.735	0.794			
PV	0.898	0.122	0.701	0.805	0.816		
SN	0.216	0.103	0.201	0.109	0.130	0.138	
SQ	0.768	0.086	0.636	0.866	0.784	0.870	0.094

The structural model, or inner model in PLS-SEM, outlines the relationships between latent variables through their path coefficients [42]. After assessing the measurement model, the next step involves evaluating collinearity, path coefficients, R^2 values, and effect sizes (f^2) [42]. Figure 3 and Table 6 present PLS bootstrapping results, including Beta values, t-statistics, p-values, hypothesis outcomes, confidence intervals, f^2 values, and VIF scores. Figure 3 provides a visual summary of the model's predictive strength and statistical significance.

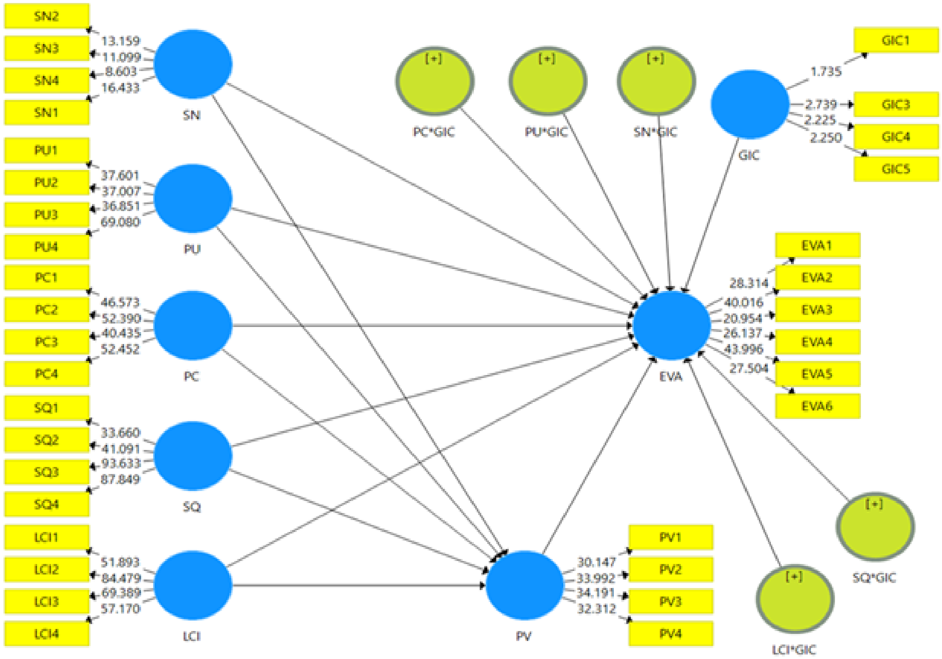

Figure 3. PLS Bootstrapping results

Table 6. Bootstrapping results 1

	Hypothesis	Std. Beta	Std. Error	T values	P values	Decision
H1	SN -> EVA	0.090	0.030	2.973	0.002	Supported
H2	PU -> EVA	0.161	0.053	3.059	0.001	Supported
H3	PC -> EVA	0.118	0.049	2.401	0.008	Supported
H4	SQ -> EVA	0.100	0.048	2.071	0.019	Supported
H5	LCI -> EVA	0.156	0.041	3.787	0.000	Supported
H6	SN -> PV -> EVA	0.001	0.012	0.077	0.469	Rejected
H7	PU -> PV -> EVA	0.084	0.023	3.569	0.000	Supported
H8	PC -> PV -> EVA	0.046	0.021	2.204	0.014	Supported
H9	SQ -> PV -> EVA	0.146	0.031	4.718	0.000	Supported
H10	LCI -> PV -> EVA	0.055	0.017	3.275	0.001	Supported

The first step in assessing the structural model involves evaluating collinearity to ensure the reliability of latent variable analysis. Addressing collinearity is crucial to prevent distortions in the estimated relationships between constructs. Variance Inflation Factor (VIF) values were used to assess collinearity, with a recommended threshold of 3.3, as suggested by [46]. As shown in Table 7, all inner VIF values for the examined constructs ranged between 2.078 and 3.151, indicating that collinearity is not a concern. Since all values remain below the established threshold, the structural model is free from multicollinearity issues, ensuring the robustness of subsequent hypothesis testing.

Bootstrapping was applied to generate path coefficient estimates to test the hypothesized relationships within the structural model, as shown in Table 7. In Partial Least Squares (PLS), bootstrapping is a nonparametric resampling method that repeatedly draws random samples with replacement from the original dataset to estimate standard errors and assess hypothesis significance [42]. Following the guidelines of [47], 1,000 subsamples were generated using Smart PLS 3.3, with a one-tailed test at a 0.05 significance level. According to [48], the critical value for one-tailed testing at $\alpha = 0.05$ is 1.645, which serves as the threshold for determining statistical significance.

The results indicate that all standardized path coefficients lie within the acceptable range of –1 to +1, specifically between 0.001 and 0.161. Higher values approaching +1 indicate stronger positive relationships, while values near zero suggest weaker associations [42]. The computed t-values for all paths met or exceeded the critical threshold of 1.645, confirming statistical significance for the proposed relationships. Table 7, a comprehensive summary of these results, is provided in the section, supporting the validity and reliability of the hypothesized paths within the research model.

The next step in evaluating the structural model involves assessing its predictive accuracy by analyzing the coefficient of determination (R^2). The R^2 value, which ranges from 0 to 1, indicates the proportion of variance in the dependent variable that is explained by the independent variables. A higher R^2 value suggests a greater level of predictive accuracy, reflecting the model's ability to explain variations in EV adoption [42].
To assess the predictive power of the model, Smart PLS was used to compute the R^2 values, in Table 6. Following the standards established by [49], the interpretation of R^2 values is categorized as follows:

- 0.02 means Weak predictive accuracy
- 0.13 means Moderate predictive accuracy
- 0.26 or higher means Substantial predictive accuracy

As illustrated in Table 7, the R^2 value for EV Adoption.

Table 7. Analysis results

Hypothesis	Confidence Intervals Lower	Confidence Intervals Upper	f^2	Effect size	VIF	R^2
H1	0.041	0.141	0.298	Medium	2.631	0.662
H2	0.073	0.255	0.292	Medium	2.078	
H3	0.040	0.209	0.207	Medium	3.151	
H4	0.018	0.174	0.109	Weak	2.861	
H5	0.089	0.216	0.420	Substantial	2.893	
H6	-0.020	0.020				
H7	0.046	0.121				
H8	0.010	0.081				
H9	0.098	0.199				
H10	0.030	0.083				

(EVA) falls within the substantial category, confirming the model’s strong predictive capability in explaining EV adoption in Oman. These results validate the robustness of the research framework and its effectiveness in capturing the key determinants influencing EV adoption.

The effect sizes, denoted by the symbol f2, have been assessed at this point. When it comes to the relative influence of a predictor construct on endogenous constructs, the value of f2 is tied to this relationship. According to [50], it is essential to provide not just the p-value but also the substantive significance (effect size) and the statistical significance (p-value) [50]. This is in addition to the fact that the p-value should be stated. In addition, a guideline established by [51] has been adhered to to measure the size of the effect. Cohen (1988) found that the values of 0.02, 0.15, and 0.35 reflect small, medium, and substantial effects, respectively. These values are based on the findings of the research [51] conducted. As can be viewed in Table 7, H4 has f^2 values greater than 0.02, which indicates a weak effect, while H1, H2, and H3 have f2 values more than .15, which indicates a medium size effect, while H4 and H5 have f2 values greater than.35, indicating a substantial size of effect.

After testing the direct effect, the moderation hypothesis is tested. A moderator is characterized as a third construct that can change or affect the relationship between independent and dependent variables [42], [52]. This study used continuous types of data, as moderation and analysis are carried out using the Smart PLS 3.3.

Moderation assessment follows the Orthogonalizing Approach [53]. This approach is based on the indicator approach and requires creating all product indicators of interaction terms [48] (see Figure 3 for the excluded moderator).

Following the assessment of direct effects, the study examined the moderating role of Government Innovation Capability (GIC) in the structural model. A moderator is a variable that can influence the strength or direction of the relationship between independent and dependent constructs [42], [52]. Using continuous data, the analysis was conducted in Smart PLS 3.3, applying the Orthogonalizing Approach [53], which constructs interaction terms between the moderator and predictor variables [48]. Figure 3 illustrates the model without the moderator.

The R^2 value increased from 0.628 (without the moderator) to 0.640 (with the moderator), as shown in Table 8. This change indicates that the inclusion of GIC adds explanatory value to the model. Based on established guidelines [54], the effect size is considered large, confirming the significance of the moderator's influence.

Table 8. R Square change

R^2 included moderator	R^2 excluded moderator
0.688	0.662

Further analysis of the moderation effects is presented in Table 9. The results show that GIC significantly moderates the relationships between Perceived Usefulness (PU), Perceived Compatibility (PC), and Lack of Charging Infrastructure (LCI) with EV adoption, as all three interactions are statistically significant with small-to-moderate effect sizes. However, no significant moderation effect was observed for the paths involving Social Norms (SN) and System Quality (SQ), indicating that GIC does not influence these relationships.

Table 9. Moderator model assessment

Hypothesis		Std. Beta	T values	P values	Decision
H6a	GIC x SN -> EVA	0.065	1.498	0.067	Rejected
H6b	GIC x PU -> EVA	0.141	2.555	0.005	Supported
H6c	GIC x PC -> EVA	0.217	2.693	0.004	Supported
H6d		0.012	0.183	0.428	Rejected
H6e		0.132	2.915	0.002	Supported

These findings underscore the importance of government innovation capability in enhancing the influence of certain adoption factors, particularly those related to perceived value and infrastructure. While some factors, like social norms and system quality, act independently of policy innovation, others, such as PU, PC, and LCI, benefit from stronger institutional support. This calls for a dual strategy that addresses both individual-level perceptions and system-level challenges, enabling a more holistic approach to accelerating EV adoption in Oman.

5. Conclusion and future work

The research establishes strong evidence regarding what drives the adoption of electric vehicles (EVs) in Oman by demonstrating how personal factors interact with technological aspects and government policies. Social Norms, along with Perceived Usefulness, served as notable predictive factors that demonstrate consumers' response to cultural standards and their perceived advantages of buying products. Personal IT Competency, together with System Quality, both had positive effects on adoption because digital skills and reliable technology systems play essential roles. The widespread adoption of electric vehicles remains limited because people struggle to access charging stations. Perceived Value functions as an intermediary factor, which demonstrates that persons who understand the practical benefits of EVs will adopt them, yet Social Norms and infrastructure influence adoption independently from the value perception.

The main value of this research emerges from its discovery of Government Innovation Capability (GIC) as a moderating factor. GIC reinforces the impact of System Quality while reducing the negative effects of limited infrastructure, making institutional support a vital factor. However, variables like Perceived Usefulness and IT Competency appear to drive adoption independently of government action, indicating that market-based strategies should complement policy efforts. These findings underscore the need for a dual approach—enhancing public awareness and perceived value while also addressing structural barriers through investments in smart infrastructure, charging networks, and supportive policies. A coordinated effort between government, industry, and consumers is essential to building a sustainable and technologically advanced EV ecosystem in Oman.

Despite its contributions, the study has several limitations. The research primarily focused on regulatory institutions, excluding manufacturers, consumers, and environmental organizations whose perspectives could provide additional insights. The cross-sectional design and short data collection period may also limit the understanding of long-term adoption trends. To address these gaps, future research should adopt a broader stakeholder approach, incorporating diverse viewpoints through mixed methods. Longitudinal and comparative studies across different regions can further clarify how context shapes adoption behavior, enabling the development of more targeted and effective policy interventions to accelerate EV adoption and promote sustainable mobility.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

Hamad Abdullah Alsalmi: Conceptualized the research idea, conducted the literature review, and contributed to the methodology design. He was also responsible for data collection and analysis, and drafted the initial version of the manuscript.

Sivadass Thiruchelvam: Provided guidance on the research framework, contributed to the interpretation of results, and assisted in refining the manuscript's structure and content. He also played a key role in reviewing and editing the final manuscript.

Firas Basim Ismail: Contributed to the development of the theoretical framework and provided insights into the technological aspects of electric vehicle adoption. He assisted with data analysis and contributed to writing specific sections of the manuscript.

Omar Munaf Tawfeeq: Provided critical feedback on the research design and methodology. He contributed to the discussion of findings and helped in revising the manuscript for clarity and coherence.

All authors have read and approved the final manuscript.

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