Trust in Range Estimation System in Battery Electric Vehicles – A Mixed Approach

Jiyao Wang, Ran Tu, Ange Wang and Dengbo He

***Abstract*—The electrification of vehicle power systems has become a dominant trend worldwide. However, with current technologies, range anxiety is still a major obstacle to the popularization of battery electric vehicles (BEVs). Previous research has found that users' trust in the BEVs' range estimation system (RES) is associated with their range anxiety. However, influential factors of trust in RES have not yet been explored. Thus, a questionnaire was designed to model the factors that are directly (i.e., implicit factors) and indirectly (i.e., explicit factors) associated with BEV users' trust in RES. Following the three-layer automation trust framework (i.e., dispositional trust, situational trust, and learned trust), a questionnaire was designed and administrated online. In total, 367 valid samples were collected from BEV users in mainland China. A mixed approach combining Bayesian network and regression analyses (i.e., BN-regression mixed approach) was proposed to explore the potential topological *relationships* among factors. Four implicit factors (i.e., sensitivity to BEV brand, knowledge of RES, users' emotional stability and trust in the battery estimation system of their phones) have been found to be directly associated with BEV users' trust in RES. Further, four explicit factors (i.e., users' highest education, regional EV infrastructure development, BEV brand, and household income) were found to be indirectly associated with users' trust in RES. This study further demonstrates the effectiveness of using BN-regression mixed approach to explore topological relationships among social-psychological factors. Future strategies aiming to modulate trust in RES can target towards factors in different levels of the topological structure.**

***Index Terms*—Electric Vehicles, Range Anxiety, Trust, Bayesian Network.**

I. INTRODUCTION

BATTERY electric vehicles (BEVs) have been promoted worldwide over the last several years. According to a roadmap proposed by China Government in 2020 [1], by 2035, China's new energy vehicles will account for over 50% of total vehicle sales, of which, 95% will be BEVs. However, the growth of the BEV market is slower than the general market forecasts [2], particularly because the infrastructure for large deployment of BEVs is not yet matured, leading to range anxiety among users or potential users of BEVs. Range anxiety has been defined as "*a stressful experience of a present or anticipated range situation, when the range resources and personal resources available to effectively manage the situation (e.g., increase available range) are perceived to be insufficient.*" [3]. In other words, range anxiety, as a psychological state, will appear when the BEV drivers become uncertain about whether they can reach their destination with the remaining battery level.

Technically, range anxiety can be alleviated through the optimization of charging station distributions (e.g., [4]), and through technical solutions, such as increasing the battery capacity in EVs (e.g., [5]) and increasing the charging speed of vehicles [6]. However, updating the hardware of BEVs and charging infrastructure is a costly and lengthy process and it may not be the only solution to range anxiety. Actually, in China, the average range of BEVs sold in 2022 is 359 kilometers [1], but in 2021, for 24 major cities in China, the average density of charging facilities is over 21.5 stations/km^2 [7]. Thus, the reward of increasing the density of the charging stations may be limited and the range anxiety becomes more of a psychological problem than a technical problem.

In BEVs, drivers rely on range estimation systems (RESs) to estimate the reachable distance of BEVs. However, the RES may not always be reliable. Several factors can affect the accuracy of RES, including road type (e.g., urban or rural), natural environment (e.g., temperature and weather), and driving style (e.g., aggressive or conservative). The degraded range estimation accuracy can lower drivers' trust in RES [8], which leads to range anxiety in BEVs [3]. However, factors affecting trust in RESs have not yet been fully explored.

Thus, through an online questionnaire, we explored the potential factors affecting users' trust in RES [9]. The significant factors were identified using a regression model selected based on backward stepwise selection. However, the regression model was not able to capture the complex topological structures within the factors [10]. In other words, some factors explored in the questionnaire may indirectly affect users' trust in RES but may have been abandoned. To overcome these limitations, some researchers tried to use linear regression methods with complex topological structures (e.g., structure equation model (SEM) [11]). However, the SEM strongly relies on the well-structured data format and pre-assumptions on the relationships between latent variables, which is unsuitable if factors can only be measured using the non-Likert-scale type of questions (e.g., age and knowledge) and when there are no pre-

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assumptions about the relationships between the factors.

To bridge the gaps mentioned above, in this study, we adopted a mixed approach combining Bayesian network (BN) and regression analyses (BN-regression mixed approach). The BN was first proposed by Judea Pearl [12] and has been used in the transportation and psychological domain in the past few years (e.g., [13]). BN is a probabilistic graphical model that is capable of modeling inter-correlated independent variables based on their attribute changes (specified by conditional probability) and can be used to interpret the heterogeneous influence of the changes on the independent variable. In BN, the effects of the independent variables can be observed by the conditional marginal probability, organized as an informative topological network. Thus, BN can be used to guide the choice of predictors and dependent variables in regression analyses, for the purpose of constructing a theoretical framework.

In this current study, additional survey samples were collected to expand the dataset used in [9]. Then a BN model was built to explore the structured dependency relationships among influential factors of users' trust in RES. Following the BN models, regression analyses were conducted to explore the relationships within each sub-network identified by BN and identify the significant variables. The main contributions of this paper are two-fold: 1) To the best of our knowledge, this study (including the part that has been reported in [9]) is the first attempt to assess factors affecting BEV users' trust in RES; 2) this is the first time the BN-regression mixed approach was introduced to investigate how psychological variables are associated with users' trust in technologies. The proposed analysis framework is highly transferable and can provide insights into survey data analysis in future studies.

II. Related Work

A. Attitudes towards RES and Range Anxiety in BEVs

Previous work found that range anxiety is more severe among new BEV users [14]. To explain this phenomenon, Rauh, et al. [3] suggested that one of the major differences between experienced and new users is that the experienced users are more aware of the solutions to extend the BEV range under different energy conditions. Rauh, et al. [3] further proposed a range anxiety model that takes the influence of route familiarity [15], the convenience of energy replenishment networks [16], and user's geographical location (such as urban or suburban [17]) into consideration.

The core concept of the range anxiety model by Rauh, et al. [3] is the comfort range, which can be defined as the range comfort zone without causing range stress. As the only tool that can provide the states of the BEV range, drivers' attitudes towards and understanding of the RES are critical influential factors of comfort range, which were found to be associated with several factors. For example, research found that both personal control of emotions [18], and internal control points [15] can affect the comfortable mileage accepted by BEV users. In our previous work [9], we introduced the trust framework by Hoff and Bashir [19] to explain the formation of BEV users' trust in RES. However, this work can only inform the correlation between factors and trust in RES – the topological structure between variables was ignored and some factors had to be abandoned to avoid the multicollinearity problem in the linear models.

B. Trust in Driving Automation

Trust is commonly defined as "*the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability*" [20]. Synthesizing existing literature, Hoff and Bashir [19] proposed a three-layered framework to explain potential factors of users' trust in automation. Specifically, dispositional trust is defined as "*long-term tendencies arising from both biological and environmental influences*" (e.g., age and culture); situational trust is related to both internal factors (i.e., transitory context characteristics) and external factors (i.e., types of the system, its complexity and the difficulty of the tasks); and learned trust refers to "*an operators' evaluation of the systems learned from past experience or current interactions*" (e.g., knowledge of the system).

A large body of research has focused on trust in automation from different perspectives of view. For example, [14] revealed some neurological mechanisms related to users' trust in technologies. Other studies focused on the formation of trust in automation and factors influencing the level of trust. For example, [21] investigated how the mental model of automation can influence users' trust in it.

However, influential factors of trust in RES have not yet been studied. The RES can be treated as a specific type of automation that estimates the status of the power system based on battery parameters. However, RES is different from well-studied advanced driving assistant systems (ADAS, for example, lane keeping assist and adaptive cruise control). ADAS is reliable in most cases but can lead to catastrophic outcomes if fails [22]; while the accuracy of RES varies due to the complexity of driving conditions (e.g., battery aging, extreme temperature, driving style, etc [23]), but rarely leads to safety-critical scenarios. Thus, there are two open research questions: RQ1: can we model users' trust in RES following the framework of trust in automation? RQ2: are there differences in factors influencing users' trust in RES and trust in ADAS?

III. Data Source

A. Questionnaire Design

Referring to the three-layered framework of trust in the automation [19] and results from [9], a questionnaire (Table 1) was designed to investigate influential factors of BEV drivers' trust in RESs. The detail of the questionnaire was reported in [9], including the factor selection based on the three-layer framework in Hoff and Bashir [19]. However, for readers' convenience, we list the candidate factors here again. Specifically, the dispositional-trust-related factors include drivers' demographic information (i.e., age, gender, income, and education) and their complacency towards automation, sensitivity to brands, and personality. The situational-trust-related factors include BEVs' brand, system usability, and driving regions. The learned-trust-related factors include driving frequency, system knowledge, and trust toward smartphones. All questions and factors are listed in Table 1. As the study is targeted towards BEV users in mainland China, the survey was translated into Chinese to distribute online.

On top of the three-layer trust framework, from the perspective of policy design and in-vehicle interface design, all factors were categorized as explicit (i.e., ones that can be objectively assessed, including *Age*, *Gender*, *Education*, *Infrastructure*, *Temperature*, *Frequency*, *Band*, and *Income*) and implicit factors (i.e., ones that can hardly be obtained directly, including *Knowledge*, *Emotional Stability*, *BEV Trust*, *Phone Trust*, *Usability*, *Complacency*, and *Trust Sensitivity*).

To evaluate users' knowledge of the BEVs, eight questions were designed, including: 1) "Compared to the slight energy regeneration mode, one-pedal (or strong energy regeneration) mode reduces the power of BEVs"; 2) "The battery capacity will be higher at the temperature of 25ºC compared to that at 2ºC"; 3) "The BEV with the lithium iron phosphate battery performs better in low temperatures than that of the ternary Lithium-ion battery"; 4) "The range of a BEV is longer at a constant speed of 90 km/h than at 50 km/h"; 5) "The estimated range will be shorter on a clear city road compared to that on a congested city road"; 6) "The estimated range will be longer if you always accelerate fast and brake intensively"; 7) "The time it takes to charge an electric vehicle from 20% to 40% is similar to the time it takes to charge from 80% to 100%"; 8) "The actual range of a BEV is not related with its power mode (i.e., energy regeneration strength)".

TABLE I

QUESTIONS, EXTRACTED VARIABLES, DISTRIBUTIONS OF RAW DATA AND THE DISCRETIZED DATA

Questions	Variables	Distribution
Q1: [FI] Date of birth	Age[D] [24]	Mean: 26.9 (SD: 5.4, min: 18, max: 48) • ≥ 35 (n=65, 17.8%) • ≥ 25 & < 35 (n=220, 89.9%) • < 25 (n=82, 22.3%)
Q2: [SC] Gender at birth	Gender[D] [25]	• Male (n=256, 69.8%) • Female (n=111, 30.2%)
Q3: [SC] Please describe the highest level of education you have completed	Education[D] [26]	• Some middle/high schools or less (n=62, 16.9%) • Associate degree (n=88, 24%) • Bachelor's degree and above (n=217, 59.1%)
Q4: [FI] Please indicate the province you drive the most	Infrastructure[S] [19]	• Well developed (n=143, 39%) • Average (n=155, 42.2%) • Less developed (n=69, 18.8%)
	Temperature[S] [19]	• North (n=90, 45.5%) • Central (n=110, 30%) • South (n=167,24.5%)
Q5: [SC] How frequently do your drive BEVs	Frequency[L] [27]	• Frequently (n=340, 92.6%) • Infrequent (n=27, 7.4%)
Q6: [FI] The brand of the BEV you drive most frequently - The BEV model, publishing year, configurations, maximum mileage were also collected, but were only used for quality checking in the survey.	Vehicle Brand[S] [28]	• Tesla (n=118, 32.2%) • BYD (n=91, 24.8%) • Wuling (n=64, 17.4%) • NIO (n=38, 10.4%) • Others (n=56, 15.2%)
Q7: [SC] Please describe your annual family income level (Chinese Yuan)	Income[D] [29]	• ≥ 40K (n=163, 44.4%) • ≥ 14K & < 40K (n=115, 31.3%) • < 14K (n=89, 24.3%)
Q8: [SC] Please judge the correctness of the statements. - Eight statements (i = 1 to 8) - Correctness of responses (t_i=1, if correct; t_i=2, if wrong) - Confidence level (c_i): 0 ("unsure") to 10 ("pretty sure") - Knowledge score = $\sum_{i=1}^{8} t_i * c_i$ (ranges from -80 to 80)	Knowledge[L] [30]	Mean: -19.8 (SD: 30.5, min: -66, max: 80) • ≥ 1 (n= 95, 25.9%) • ≥ -22.0 & < 1.0 (n=90, 24.5%) • ≥ -48.0 & < -22.0 (n=100, 27.3%) • < -48.0 (n=82, 22.3%)
Q9: [LS] The Ten Item Personality Questionnaire (TIPI) [31] - Focus on emotional stability - Calculated following the method in [31] - Cronbach α = 0.767 - KMO = 0.806 - *p* value of Bartlett's Sphericity test <.0001	Emotional Stability[D] [32]	• Extremely unstable (n= 55, 15%) • Unstable (n=128, 34.9%) • Stable (n=96, 26.1%) • Extremely stable (n=88, 24%)
Q10: [LS] Five-item facets of trustworthiness (FIFT) [26] targeting towards users' trust in RES of the BEV they drive the most, revised adaptively from 6 points to 7 points following [33]. The average of the five facets was used following [32]. - 1 ("not at all") to 7 "extremely" - Cronbach α = 0.657 - KMO = 0.77 - *p*-value of Bartlett's Sphericity test <.0001	BEV Trust	Mean: 5.19 (SD: 0.76, min: 2.2, max: 7) • ≥ 5.6 (n=120, 32.7%) • ≥ 5.2 & < 5.6 (n=89, 24.3%) • ≥ 4.8 & < 5.2 (n=80, 21.8%) • < 4.8 (n=78, 21.2%)
Q11: [LS] A FIFT [26] targeting towards battery estimation system (BES) of the smartphone they use the most. The mean of five facets was used [32]. - 1 ("not at all") to 7 "extremely"	Phone Trust[L] [9]	Mean: 5.39 (SD: 0.74, min: 2.6, max: 7.0) • ≥ 5.8 (n= 114, 31.1%) • ≥ 5.4 & < 5.8 (n=87, 23.7%) • ≥ 5.0 & < 5.4 (n=83, 22.6%)

- Cronbach α = 0.652 - KMO = 0.765 - p value of Bartlett's Sphericity test <.0001		• < 5.0 (n=83, 22.6%)
Q12: [LS] System Usability Scale (SUS) questionnaire [35] regarding RES of the BEV they drive the most - 0: "low" to 100: "high" - Cronbach α = 0.791 - KMO = 0.835 - p value of Bartlett's Sphericity test <.0001	Usability^{S} [34]	Mean: 54.7 (SD: 17.4, min: 25, max: 100) • ≥ 68.8 (n= 108, 29.4%) • ≥ 50 & < 68.8 (n=94, 25.6%) • ≥ 40.6 & < 50 (n=89, 24.3%) • < 40.6 (n=76, 20.7%)
Q13: [LS] The 10-item automation induced complacency potential rating scale (AICP-R) [37] - 0: "low" to 25: "high" - Cronbach α = 0.650 - KMO = 0.627 - p value of Bartlett's Sphericity test <.0001	Complacency^{D} [36]	Mean: 17.7 (SD: 1.79, min: 9, max: 24) • ≥ 19 (n= 122, 33.2%) • ≥ 17.5 & < 19 (n=98, 26.7%) • ≥ 16.5 & < 17.5 (n=85, 23.2%) • < 16.5 (n=62, 16.9%)
Q14: [LS] Please indicate your confidence in the range estimation system and battery system of the following BEVs based on your impressions or experience - Six questions (i = 1 to 6) - Trust score in each brand (t_i): 1 ("not at all") to 7 ("extremely") - Sensitivity score = $max(t_i) - min(t_i)$ (ranges from 0 to 6)	Brand Sensitivity^{D} [28]	Mean: 1.9 (SD: 1.2, min: 0, max: 6) • ≥ 2 (n= 212, 57.8%) • ≥ 1 & < 2 (n=124, 33.8%) • < 1 (n=31, 8.4%)

Note: Abbreviations of question types are as follows*: **FI**: Fill-in-text; **SC**: Single-choice; **MC**: Multiple-choice; **LS**: Likert scale; **TF**: True or false. **SD** standards for standard deviation. The superscript in the third column indicates the discretizing method used in this variable. In the second column, D, S and L stands for dispositional-trust-related, situational-trust-related and learned-trust-related factors, respectively. The citations in the second column list the research that inspired our choice of the variable.*

Considering the large variance of nature environment (e.g., temperature) and infrastructure development levels in mainland China, the impact of geographical region on users' attitudes towards the BEVs must be considered. These two variables were extracted based on the EV infrastructure development [16] and the historical temperature [38] of the provinces that the respondents drove the most. The variable *Infrastructure* has three levels, i.e., "*Less developed*" (e.g., Jiangsu, Shanghai, Beijing), "Average" (e.g., Hunan, Sichuan, Tianjing), and "Well developed" (e.g., Jiangxi, Jilin, Liaoning). The *Temperature* has three levels, i.e., "North" (e.g., Liaoning, Qinghai, Heilongjiang), "Central" (e.g., Shandong, Henan, Hebei), and "South" (e.g., Guangdong, Zhejiang, Hubei). Further, considering that users' sensitivity to BEV brand reputation may affect their trust in RES [28], the questionnaire inquiries about respondents' ratings of six bestselling BEVs in Chinese market with a 7-point Likert scale (i.e., 1: "not at all" to 7: "extremely") and we used the range of the responses (the gap between the highest score and the lowest score) for each participant as an indicator of their sensitivity to brands.

B. Participants

Approved by the Human and Artefacts Research Ethics Committee at the Hong Kong University of Science and Technology (protocol number: HREP-2022-0051), all participants were recruited via social media on the Internet and 966 participants completed the questionnaire. We then screened the answers based on two quality-checking questions (e.g., "*please select 4 if you are reading the questionnaire*") and the consistency of the answers in Q6 (i.e., whether the brand, model, publishing year, configurations and maximum mileage of the BEV matches). As a result, 389 participants failed the two attention check questions and 132 participants failed to provide consistent answers, and 445 samples were kept for analyses. Then, we removed samples from drivers who do not own BEVs, and 403 samples were kept. Next, as commercial vehicle drivers may have developed different strategies for using BEVs, we removed the samples from the ride-hailing or taxi drivers and 367 samples were kept for analyses (Male: 256; Female: 111). These 367 drivers received a compensation of 5 Chinese Yuan for their completion of the 20-minute-long questionnaire. The summary of collected data is presented in Table I. It should be noted that our participants were relatively young (<48 years old), potentially due to the characteristics of BEV population or our recruiting methods. Given that age can be associated with trust in the automation [24], future research is still needed to scrutinize the age effect. Further, to validate the reliability and validity of our collected data, we performed reliability and validity test on questions adopted from standard questionnaires (i.e., Q9 to Q13) with Cronbach, Kaiser-Meyer-Olkin value (KMO), and Bartlett's Sphericity test [39] (see Table I) – all reached satisfactory levels [40].

IV. ANALYSIS METHODOLOGY

The overall research framework is presented in Fig. 1.

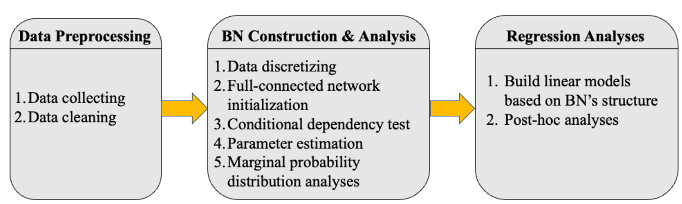

Fig. 1. Research flow framework.

A. Construction of Bayesian Network Model

BN is a probabilistic graph model based on Bayes' theorem and is known for its capacity to distinctly demonstrate the conditional dependencies between variables [41]. Fig. 2 provides an example of the BN structure. In the graph, each variable is represented as a node, and the relationships between nodes are defined as edges linking each pair of nodes. In edges, the confidential dependency can either be observed from the dataset or be preset by the prior knowledge [41]. Fig. 2 provides an example of the topological structure in BN.

The determination of dependency structure and its associated conditional probability tables (CPTs) are critical for the construction of a BN. There are three approaches for BN structure construction [42], i.e., the data-based approach that learns the structure and CPTs from a large amount of historical data automatically; the prior-knowledge-based approach that relies on experts' prior knowledge to identify the BN structure; and the combination of both (i.e., hybrid approach). Although the data-based approach can get the most informative structure and satisfying prediction performance without prior domain knowledge, it is often restricted by the quality and volume of data and the generated structure can be hard to interpret [43]. While the prior-knowledge-based approach is inefficient and may not be able to identify the dependency relationship structure accurately. Thus, in this work, we adopted the hybrid approach using the "*pgmpy*" package [44] in Python 3.8 and verified all edges using dependency tests [45].

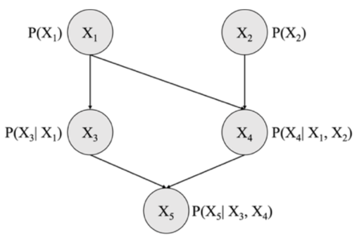

Fig. 2. An example of the BN model.

Specifically, we used prior domain knowledge based on the trust framework proposed by Hoff and Bashir [19], our preliminary analysis [9], as well as other relevant literature [29] to select candidate variables. As the construction of BN relies on the estimation of conditional probability, the continuous data was first discretized using two strategies. For the continuous variables that have commonly accepted cut-off scores, we directly referred to these scores (including *Age* [46] and *Emotional Stability* referring to [47]). For the rest of the continuous variables, to balance the model fitting performance (i.e., to keep enough data in every single level of the variables) and the information loss (due to the discretization of the continuous variables), we discretized them into four categories at their 25%, 50%, and 75% quantile locations (i.e., for *Brand Sensitivity*, *Knowledge*, *Complacency*, *BEV Trust, Phone Trust* and *Usability*). Note that the 50% and 75% percentiles of *Brand Sensitivity* were the same, so it has only three categories.

Then, explicit and implicit factors were assigned into two different layers (i.e., explicit layer and implicit layer) and each pair of variables between the layers were fully connected, without prior conditional probability distributions (CPDs); but the variables within a layer were disconnected, given that we were only interested in the topological structure explaining how a variable can influence BEV Trust. The connections between explicit factors and BEV Trust were removed to satisfy the acyclicity assumption of BN. Then we used data-driven methods to prune the network based on an automated constraint conditional dependency searching [48] and Chi-Square test. Only significant (p<.05) conditional dependences were reserved in BN and the CPTs of the BN were estimated with the Bayesian parameter estimation method [44]. Finally, to extract the marginal probabilistic distribution (MPD) given specific evidence (i.e., a specific level of a variable), a heuristic function, *MinFill* [50] was used to decompose the joint influence of the parental variables in each sub-structure.

B. Regression Analyses

Following BN, to quantify the relationships among variables, regression analyses were conducted for all hierarchical sub-structures in BN. Depending on the type of dependent variables, mixed linear regression models (using Proc MIXED procedure) and logistic regression models (using Proc GENMOD procedure) were implemented in "*SAS OnDemand for Academics*". Specifically, for all sub-structure in BN (Fig. 3), we built regression models with the node itself as the dependent variable and all its parental nodes as independent variables. For example, when *Brand Sensitivity* was used as the dependent variable, *Infrastructure* and *Brand* were used as the dependent variables. In all models, the regression analyses were based on the data before discretization, and only participant was regarded as a random variable. To avoid the multicollinearity problem, we adopted backward stepwise selection procedures based on model fitting criteria and Variance Inflation Factor (e.g., *Infrastructure* was kept but *Temperature* was abandoned in the model of *Knowledge*). Seven sub-structures were investigated. The Tukey-Kramer post-hoc tests [51] were conducted for all significant variables (p<.05) in each sub-structure.

V. Results

A. BN Results

As shown in Fig.3, explicit factors (i.e., *Education*, *Infrastructure*, *Brand*, *Temperature*, *Gender*, and *Income*) were in the top layer, and implicit factors were in the middle layer. It should be noted that, although we identified significantly seemly monotonic trends for some variables, we were not able to conclude the trends. Further regression analyses are needed.

B. Regression Analyses Results

We first provided the correlations between explicit factors (Table II) and implicit factors (Table III). Then, in regression analyses, the relationships that are statistically significant are highlighted in red in Fig. 3 and the significant post-hoc contrasts are in Fig. 4 and Table. 5. As shown in Table IV, *Emotional Stability*, *Brand Sensitivity*, *Knowledge*, *Phone Trust* were significant predictors of *BEV Trust*. Specifically, for each 10-score increase in the *Brand Sensitivity* and *Knowledge*, a 0.6-unit (95% CI: [-0.11, -0.02]) and 0.04-unit (95% CI: [-0.007, -0.003]) decrease in *BEV Trust* have been observed, respectively. At the same time, with every 1-unit increase of *Phone Trust*, *BEV Trust* increased by 0.5 units (95% CI: [0.4, 0.6]). All other statistical results and the corresponding significant (p<.05) post-hoc contrast results for the sub-structures in BN are presented in Table IV and Table V. In all following tables, *marks significant results (p<.05); DV stands for dependent variable; IV standards for independent variable.

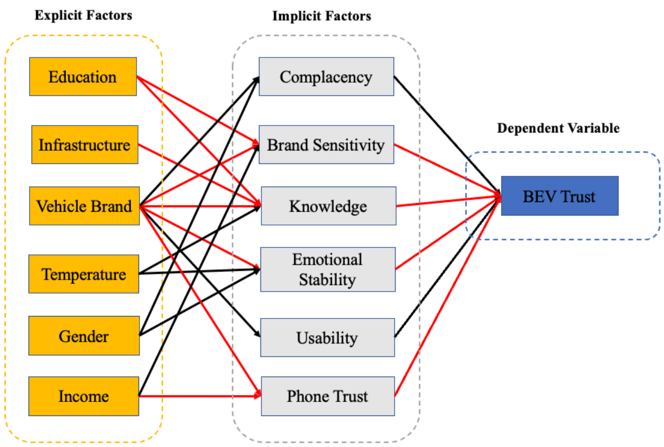

Fig. 3. The structure of the developed BN model. The red lines highlight the statistically significant relationships.

TABLE II

SPEARMAN CORRELATION MATRIX OF IMPLICIT FACTORS

	Brand Sensitivity	Knowledge	Emotional Stability	Usability	Phone Trust
Complacency	-.07	-.16*	.01	.27*	.28*
Brand Sensitivity		.05	.11*	.14*	.003
Knowledge			.16*	.12*	-.03
Emotional Stability				.45*	.21*
Usability					.48*

TABLE III

SPEARMAN CORRELATION MATRIX OF EXPLICIT FACTORS

	Infrastructure	Vehicle Brand	Temperature	Gender	Income
Education	.11*	-.04	.14*	.01	-.03
Infrastructure		-.01	.52*	.04	.03
Vehicle Brand			-.03	-.001	.06
Temperature				-.07	-.04
Gender					.05

TABLE IV

SUMMARY OF STATISTICAL RESULTS

DV	IV	F-value/χ^2-value	*p*-value
BEV Trust	Complacency	$F(1, 358) = 3.69$	.056
	Emotional Stability	$F(3, 358) = 1.46$	.0005*
	Brand Sensitivity	$F(1, 358) = 6.71$	.01*
	Knowledge	$F(1, 358) = 19.04$	<.0001*
	Phone Trust	$F(1, 358) = 108.95$	<.0001*
	Usability	$F(1, 358) = 0.01$	.9
Complacency	Gender	$F(1, 361) = 5.16$	.15
	Vehicle Brand	$F(4, 361) = 2.05$	.0005*
Brand Sensitivity	Education	$F(2, 358) = 8.73$	.0002*
	Vehicle Brand	$F(4, 358) = 5.48$	.0003*
	Income	$F(2, 358) = 2.49$	.08
Knowledge	Education	$F(2, 358) = 7.20$	.0009*
	Infrastructure	$F(2, 358) = 7.97$	.0004*
	Vehicle Brand	$F(4, 358) = 4.18$	.0025*
Emotional Stability	Vehicle Brand	$\chi^2(12) = 44.57$	<.0001*
	Gender	$\chi^2(3) = 3.93$	.3
	Temperature	$\chi^2(6) = 12.02$	.06
Usability	Vehicle Brand	$F(4, 362) = 12.42$	<.0001*
Phone Trust	Income	$F(2, 360) = 4.09$	.02*
	Vehicle Brand	$F(4, 360) = 2.90$	.02*

TABLE V

SIGNIFICANT POST-HOC RESULTS FOR DISCRETE INDEPENDENT VARIABLES

DV	IV	IV Level	IV Level compared to	Δ (95% CI)	t value	*p*-value
BEV Trust	Emotional Stability	Extremely unstable	Extremely stable	-0.32 [-0.60, -0.04]	$t(358)=-2.91$	.02*
		Unstable	Stable	-0.29 [-0.53, -0.05]	$t(358)=-3.13$	.01*
			Extremely stable	-0.33 [-0.56, -0.10]	$t(358)=-3.77$	.001*
Brand Sensitivity	Vehicle Brand	NIO	Tesla	0.91 [0.26, 1.55]	$t(358)=3.86$	.002*
		BYD	NIO	-0.90 [-1.56, -0.25]	$t(358)=-3.77$	.001*
	Education	Associate degree	Some middle/high schools or less	-0.67 [-1.15, -0.20]	$t(358)=-3.34$	.003*
		Bachelor's degree and above	Some middle/high schools or less	-0.74 [-1.16, -0.32]	$t(358)=-4.13$	.0001*
Knowledge	Infrastructure	Average	Less developed	16.50 [6.52, 26.48]	$t(358)=3.89$	.0004*
		Less developed	Well developed	-14.18 [-24.20, -4.17]	$t(358)=-3.33$	.003*
	Vehicle Brand	NIO	Others	-17.69 [-34.95, -0.43]	$t(358)=-2.81$	.041*
		Others	Tesla	14.60 [1.91, 27.28]	$t(358)=3.16$	.02*
	Education	Bachelor's degree and above	Some middle/high schools or less	15.54 [5.86, 26.23]	$t(358)=3.64$	.0007*
Usability	Vehicle Brand	BYD	NIO	-8.82 [-17.48, -0.15]	$t(362)=-2.79$	.044*
			Wuling	-10.32 [-17.64, -3.00]	$t(362)=-3.86$	.001*
		NIO	Tesla	14.31 [5.94, 22.68]	$t(362)=4.69$	<.0001*
		Others	Tesla	9.42 [2.13, 16.70]	$t(362)=3.54$	.0004*
		Tesla	Wuling	-15.81 [-22.78, -8.85]	$t(362)=-6.22$	<.0001*
Phone Trust	Income	≥ 40K	< 14K	0.25 [0.02, 0.47]	$t(360)=2.54$	.03*
	Vehicle Brand	Tesla	Wuling	-0.36 [-0.67, -0.05]	$t(360)=-3.20$	.01*
Complacency	Vehicle Brand	Tesla	Wuling	-1.2 [-1.95, -0.44]	$t(361)=-4.35$	.002*

Note: Δ = IV Level - IV Level compared to: when it is positive it means IV Level > IV Level compared to and vice versa.

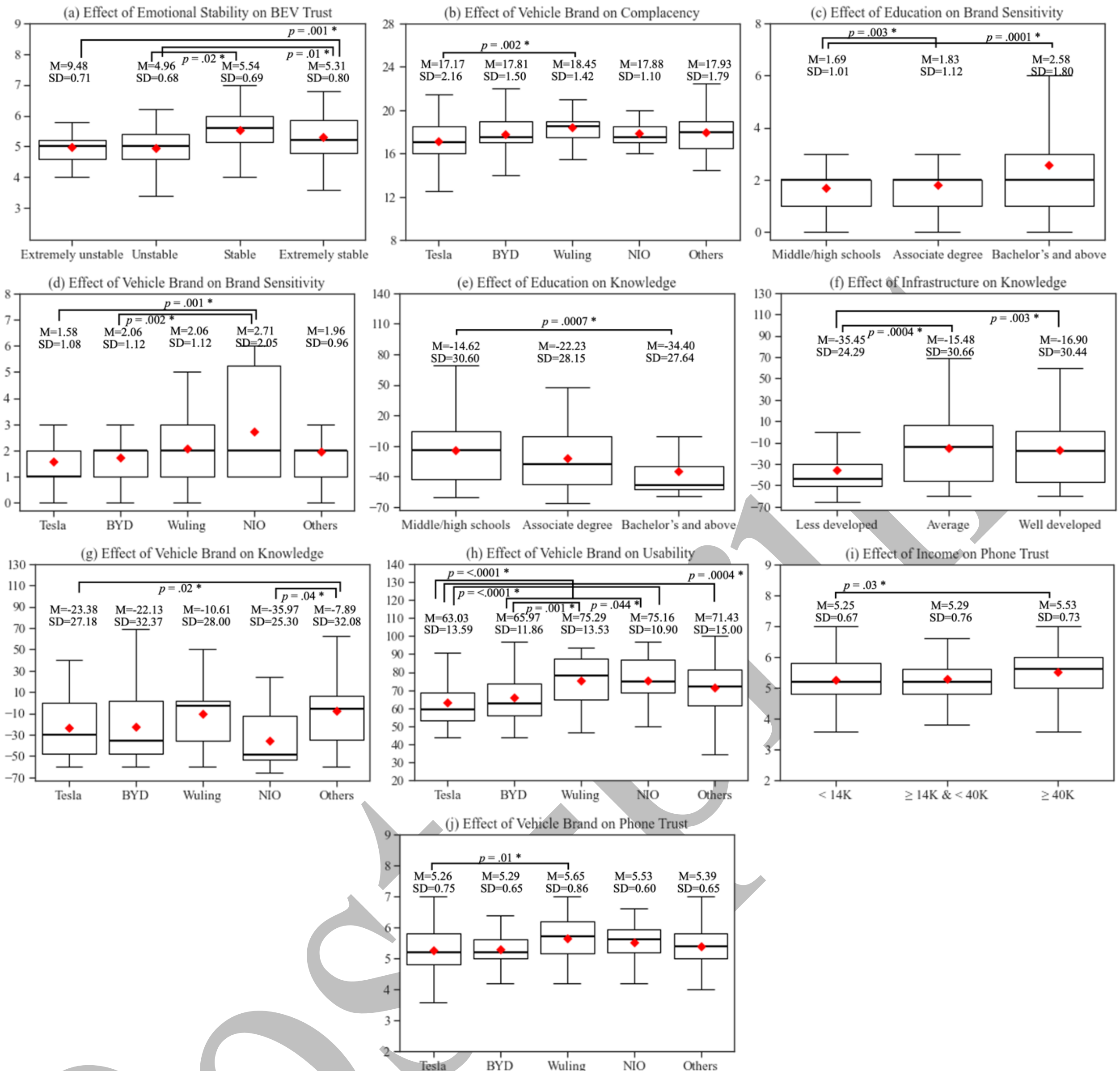

Fig. 4. The boxplots of significant effects. In this and the following plots, boxplots present the minimum, 1st quartile, median, 3rd quartile, and maximum, along with the mean depicted through a yellow triangle.

VI. Discussions

In this section, we first discussed results regarding drivers' trust in RES. Then we briefly discussed our BN-regression mixed approach as a framework.

A. BEV Users' Trust in RES

In response to RQ1, we found that the framework by Hoff and Bashir [19] can be used to explore factors that are associated with users' trust in RES of BEVs. We identified users' *Brand Sensitivity* and *Emotional Stability* from the dispositional-trust-layer, and *Knowledge* and *Phone Trust* from the learned-trust-layer as implicit factors that are directly associated with users' trust in RES (*BEV Trust*). The factors from the situational-trust-layer, including *BEVs' Brand* and *Infrastructure* were not directly associated with BEV Trust, but were indirectly associated with the above-mentioned implicit factors. Some of these factors have been identified as influential factors in users' attitudes toward other automation systems but were the first time identified as associated with trust in RES. For example, the association between knowledge and trust has been identified in previous driving-automation-related research [21]. In our study, a negative correlation between knowledge of EV and trust in RES has also been identified, indicating that at the current stage, the more the users are aware of the RES limits and functions, the less they trust in it. These results indicate the feasibility of treating RES as an automation system when investigating users' trust in it.

In addition, we have identified several direct influential factors of users' trust in RES. These factors are practically important and were under-investigated in previous research on

ADAS trust or had different effects on users' trust in ADAS. A discussion on these factors can provide insights on RQ2, i.e., whether the discrepancy exists in users' trust in ADAS and in RES. For example, users' trust in the battery system of phones (*Phone Trust*) and trust in the RES of BEVs were positively associated, indicating that trust in different battery systems can be mutually transferable. In contrast, to the best of our knowledge, no research has investigated the association between users' trust in similar ADAS systems. Future research should investigate which features of the systems have contributed to this "shared trust" and whether and when such a phenomenon can be observed in ADAS-related trust. Further, we noticed that the increase in brand sensitivity and emotional instability were associated with lower trust in RES. The relationship between emotional stability and trust is different from what has been observed in ADAS-related research [52]. It can be explained that users with higher emotional stability were more sensitive to the range uncertainty [18] and trusted less in the RES, a system that is not safety-critical; while with higher emotional stability, the users were more resistant to emotion fluctuation caused by imperfection of the ADAS and thus tended to trust the ADAS more.

Again, in response to RQ2, we did not find age to be associated with trust in RES, while age has been repeatedly found to be the influential factor of trust in ADAS [52], [53]. As mentioned, the usage of ADAS is optional, but the usage of RES is inevitable in BEVs. Thus, young users might use ADAS more and hold a more positive attitude toward ADAS; while age had no effects on users' usage or perception of RES. Future research is needed to validate our observed relationships.

As another major contribution of this study, with the help of BN, we identified a topological structure among the influential factors we identified. In general, the factors associated with trust can be categorized into two layers – explicit factors and implicit factors and we have identified interesting significant relationships between explicit and implicit layers. Firstly, users' education has been found to be associated with their brand sensitivity and their knowledge of EVs. The positive correlation between education and knowledge of EVs is not surprising. However, it is interesting to observe a negative relationship between *Education* and *Brand Sensitivity*. We assume that better-educated people were more objective in judging a product and had a less extreme judgment of it. But future research is needed to validate this hypothesis.

Further, users' knowledge of BEV has been found to be positively associated with regional EV-related infrastructure development. One would explain this as the correlation between regions and education level. However, the correlation between *Education* and *Infrastructure* was weak (Table II). Thus, it is more likely that in regions with more developed EV infrastructure, the market share of BEVs is larger and thus the users have a higher chance to learn about BEVs.

At the same time, *Vehicle Brand* was found to be associated with all implicit variables. The association between *Vehicle Brand* and *Emotional Stability* and *Knowledge* might be explained as the influence of the latter two factors on users' choice of brands, similar to how user profile is associated with the brand labels [54]. However, for the relationship between *Vehicle Brand* and *Knowledge*, there might be an alternative explanation - it is likely that some vehicle brands may provide better customer education and thus their users have better knowledge about RES. However, this hypothesis may need to be validated through observational studies. Further, the association between *Vehicle Brand* and *Phone Trust* might also be explained as the connections between the brand labels and user profiles. It is also possible that another covariant influenced users' choice of both phone and vehicle brand. For example, the users who care about the usability of their devices might have chosen a phone and a vehicle that has a better human-machine interface design, as evidenced by the moderate correlation between *Usability* and *Phone Trust* in Table II.

Lastly, it is interesting to notice that *Income* is associated with *Phone Trust* – potentially because users who had higher income may choose more expensive and better-designed phones. More research, however, is needed to validate the hypotheses and explanations proposed in our discussions.

B. BN - Regression Mixed Approach

This study adopted a novel approach to explore the influential factors of trust – the BN-regression mixed approach. First, based on BN, the dependency relationships among explicit factors, implicit factors, and trust in RES of BEVs can be established, which can guide the regression analyses. Further, multicollinearity is not an issue in BN because of the independence assumption [41]. Thus, we can include highly correlated factors in a sub-structure and then choose the most appropriate ones (or create new variables through aggregation) in the following regression analyses. Then, the regression analyses can further screen the relationships identified in BN. In summary, the two components in the mixed approach can supplement each other, generating some results that can hardly be obtained through regression models only.

Specifically, although the associations between some explicit factors and trust have been observed in previous studies (e.g., education in [26], gender in [9]), our mixed approach provided further information on how these "external" explicit factors can potentially affect respondents' trust through "internal" implicit factors (i.e., factors that reflect respondents' psychological or cognitive states) and then further affect one's trust in a system (e.g., Brand Sensitivity, Phone Trust). Our mixed approach combines data-driven and pre-knowledge to build up the topological structure. This procedure can be used to expand existing psychological models, similar to how the Technology Acceptance Model (TAM) [55] was expanded into Automation Acceptance Model (AAM) [19] - one additional layer consisting of trust and compatibility was added. In contrast, instead of relying on theoretical analyses from psychological perspectives, using our mixed approach, one might be able to generate such a structure with data only. However, carefully designed experiments may still be needed to explain the model extracted from our mixed approach theoretically.

It should also be noted that our BN-regression mixed approach can still only inform the associations between variables, but not necessarily causality. For example, *Infrastructure* is connected to *Knowledge* in Fig. 3, but this does not mean that one can affect the other. There might be a covariate that shapes the distribution of both variables. Further, a mandatory discretization of the continuous variables was needed in BN, which can be arbitrary and deviates the distributions of data in BN analyses from that in regression analyses. Thus, one should be cautious about the results from BN. Future BN approaches without requiring discretization may improve our mixed approach.

VII. Conclusions

In this study, we adapted the framework of trust in automation by Hoff and Bashir [19] to explore the potentially influential factors of *BEV Trust* through a BN-regression mixed approach. We summarize the major findings below:

- Our study has provided evidence to support the feasibility of treating RES as automation and adopting the framework by Hoff and Bashir [19] to identify potential influential factors of users' trust in it.
- We demonstrate the feasibility of using the BN-regression mixed approach to explore the topological structure among influential factors of users' trust in RES – an internal relationship among the trust-related factors has been identified and the explicit factors may influence users' trust in RES indirectly, by affecting implicit factors. The topological structure can be expanded more easily compared to regression models. Explicit variables can influence trust; but variables not included in the structure can also influence trust by affecting the implicit variables.
- The outcome of our study also provides insights into how to design strategies that moderate one's trust in RES. For example, to boost users' trust, one may consider providing user orientation (thus influencing *Knowledge*) or providing electronic devices with better battery performance (based on the association between *Phone Trust* and *BEV Trust*). These strategies should also vary between user populations. For example, given that users of vehicles with different brands have different levels of knowledge of RES, different strategies can be used to promote users' knowledge of RES.

Future research, however, should validate the relationships identified in our study by observing users' actual behaviors in on-road experiments or naturalistic studies. The topological model can also be updated or expanded if strategies to boost trust in RES are to be developed for a specific user population.

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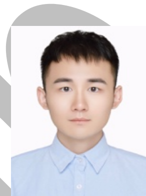

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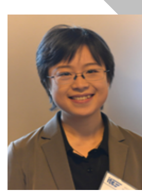

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