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A Bayesian approach to planning support on two-lane rural roads for automated vehicles: The role of geometric design in disengagement events

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ABSTRACT

This paper presents an on-road study examining the interaction between Level 2 automated vehicles (AVs) and the geometric features of two-lane rural roads. These roads constitute the largest percentage of the road network in most countries. Their complex geometric features and lack of design consistency present a significant challenge for the operation of automated vehicles (AVs). Although AV systems aim to reduce driver workload and improve road safety, their performance remains limited on these roads, often resulting in automated system disengagements that require driver intervention. Such disengagements highlight emerging challenges for road administrations regarding road readiness and the safe integration of AVs into existing infrastructure.

Based on an on-road study using two instrumented AVs, this study investigates how geometric features of Homogeneous Road Segments (HRS), including Curvature Change Rate (CCR_{HRS}), average radius, tangent length, and average parameter of vertical curves, affect driving system engagement rates. A Bayesian approach was used to quantify the relationship between road geometry indices and AV disengagements. The findings reveal that the primary factor affecting engagement status is CCR_{HRS}, showing that higher values of CCR_{HRS} (>400 gon/km) are associated with AV engagement dropping below 25%, highlighting a direct impact of geometric complexity on AV reliability. The other geometric indices have a moderate positive effect. The findings underscore that road geometry significantly affects AV reliability.

These findings have significant implications for infrastructure planning and policy. By identifying geometric thresholds that compromise AV functionality, this research supports the definition of Operational Road Sections (ORS) aligned with Operational Design Domains (ODD). The proposed model offers a practical tool for road administrations to assess road suitability for AV deployment, inform upgrading priorities, and establish design guidelines that facilitate the safe integration of AV technologies into existing rural networks. As automation advances, aligning infrastructure design with AV capabilities becomes essential for equitable and effective transport policy.

1. Introduction

The deployment of automated vehicles (AVs) on the roads is expected to have significant positive impacts in various areas, such as transport operation, safety, management or emissions (Fagnant and Kockelman, 2015; Tengilimoglu et al., 2023a; Ye et al., 2021). To achieve these benefits, an optimal performance of the autonomous driving system is required, which is expected with the introduction of fully automated vehicles, SAE Level 5, according to the Society of Automotive Engineers (SAE International, 2021). However, until these vehicles are on the roads, many challenges from different points of view, such as technological, regulatory, or ethical, must be overcome (Atakishiyev et al., 2023; Kontos et al., 2024; Cecchini et al., 2023; Moradloo et al., 2024); showing that most challenges in advancing novel technologies involve navigating situations that push systems beyond their typical capabilities. Olayode et al. (2023) argue that, in order to fully deploy autonomous vehicles within a road transportation system, the existing infrastructure requires significant improvement.

This represents a growing concern for road administrations and planning agencies, which need actionable criteria to evaluate whether existing road segments are suitable for AV operation, or whether upgrades are required to ensure safe deployment. Recent infrastructure readiness discussions by transportation agencies have emphasized that the safe deployment of automated driving systems depends not only on

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vehicle technology, but also on roadway conditions such as the consistency and condition of lane markings, traffic control devices, and geometric design features. In this context, several road authorities and international transport bodies have begun to consider assessment frameworks to evaluate whether existing road networks are adequately prepared to support progressive AV deployment (FHWA, 2021; OECD/ITF, 2023).

At this stage, vehicles with partial-automation SAE Level 2 travel on public roads, and the first vehicles equipped with SAE Level 3 have entered the market. Vehicles with partial-automation incorporate Advanced Driver Assistance Systems (ADAS) which can simultaneously control the longitudinal (e.g., adaptive cruise control, ACC) and lateral (e.g., lane keeping assist, LKA) movements. These ADAS allow executing all aspects of the driving task within its Operational Design Domain (ODD) (SAE, 2021). Then, at these levels of automation, driving is a collaboration between driver and vehicle characterized by dynamic Transfer of Control (TOC) (Seppelt and Victor, 2016; Gershon et al., 2021). Out of the ODD or if the ADAS encounters unexpected issues, the automated system disengages, and TOC is given to the driver. The main difference between the automated systems at these SAE levels is how TOC is performed: at Level 2 it is done automatically, while at Level 3, the system relays a request for intervention (Take Over Request-TOR) within short time frames. In both cases, system disengagements are a major challenge from a safety point of view. Tamakloe and Park (2023) also highlight the need for future research to focus on the development of more effective and reliable takeover systems that prioritize safety, thereby enhancing the overall safety of AVs. Beyond safety, frequent disengagements represent an operational limitation that must be considered in transport planning decisions, particularly when AVs are expected to operate in complex road environments, as rural roads.

Goodall (2024) indicated that a major challenge in determining crash rates for automated driving systems is the lack of data. The National Highway Traffic Safety Administration (NHTSA) has collected crash data since June 2021 but has not required manufacturers to report automated mileage, so crash rates cannot be calculated (Goodall, 2025). Recently, using this data set, Ding et al. (2024) have shown accident data from Level 2 and Level 3 SAE vehicles. They examined 1001 crashes involving these vehicles and found that 67% of the crashes occurred on highways and the remainder in urban areas. However, data from AV collisions on rural roads has not yet been studied.

Dixit et al. (2016) indicated that many unknowns remain regarding the factors influencing automated driving system disengagements, as well as the associated safety risks of AVs. Previous studies have pointed out that disengagements occur in response to system failure or missing functionality, such as failures in sensor and detection technology, communication systems, map calibration, or hardware (Gershon et al., 2021; Techer et al., 2019). Wang and Li (2019) noted that disengagement frequency varies considerably across technologies and road types. According to the Autonomous Disengagements Report developed by the California Department of Motor Vehicle (California Department of Motor Vehicles, 2020) 64% of disengagements were caused by road infrastructure, with errors especially occurring on horizontal curves. Tengilimoglu et al. (2023b) highlighted that the requirements of the infrastructure to facilitate AVs have not been clearly defined so far. In the short term, developing automated driving technology capable of operating on all existing roads without infrastructure upgrades appears unfeasible (ERTRAC, 2019). In that case, rural roads are one of the major challenges for AVs. SAE Level 2 vehicles are most frequently used on high-speed roads rather than rural roads, where disengagements tend to increase (Reagan et al., 2019). Hu et al. (2022) also found that most SAE Level 2 vehicles have been designed for use on limited-access interstates and freeways and in clear weather conditions.

Two-lane rural roads represent a particularly challenging environment for partial automation, as they often combine high variability in horizontal and vertical alignment, inconsistent design standards, limited signage, and degraded lane markings. These characteristics can directly affect sensor-based lane keeping and lead to frequent disengagements, making rural networks a critical but still underexplored domain for assessing real-world AV operational limitations. Specific studies have attempted to identify the parameters that affect AV performance under these kinds of roads. American Automobile Association (2020) and Reagan et al. (2020), using naturalistic driving data of SAE Level 2 vehicles revealed that LKA may struggle when encountering features commonly found on limited-access roads, such as horizontal curves, lane splits, and missing lane markings. Hu et al. (2022) performed a study focused on curves located on interstates and freeways, finding that automated systems have limited operational ability on curves, causing them to disengage automatically in challenging conditions or leading to a lack of driver confidence. A field experimentation conducted by García et al. using a SAE Level 2 vehicle showed that the current systems have difficulties operating autonomously in crest vertical curves with a parameter equal or lower than 30 m/% (García et al., 2019). García et al. (2020) noted a stronger relationship between horizontal curvature and the automated speed at which SAE Level 2 vehicles circulated. In this regard, the automated system usually disengaged with radii smaller than 450 m. Previous researchers have also indicated that both horizontal and vertical curvatures of the road have an effect on the operation of AVs systems such as the ability to detect lane marking (Marr et al., 2020; Tao, 2016) or how to perform path planning control (Eskandarian et al., 2020; Xu and Peng, 2020). Nitsche et al. (2014) indicated that sharp curves influence the safe operation of both lane assistance systems and speed control systems.

Adapting infrastructure to the requirements of automated driving requires advances in standardization, technology, investment and policy, making its study essential for the future of mobility. One step to advance in this direction was introduced by García et al. (2023), indicating that the concept of ODD can be unhelpful to Road Administrations and Operators, who need to know how are going to operate AVs along the road segment. Under this line, they defined the concept of the Operational Road Section (ORS). ORS was defined as a road segment compatible with the ODDs of the majority of automated vehicles. They provided a theoretical framework for characterizing ORSs along rural roads; however, the specific variables needed to define this ODD to identify these sections remain unexplored. Pappalardo et al. (2022) also conducted an experimental study and concluded that several road and environmental factors—particularly road curvature, pavement markings, and rain—significantly affect the fault probability of lane support systems (LSS), emphasizing the need for improved infrastructure and localized weather monitoring to safely extend the operational design domain (ODD) of autonomous vehicles.

The ORS concept can be associated with consistency in the geometric design. Then, as a geometric design consistency refers to how well road characteristics align with driver expectations and road behavior (Llopis-Castelló et al., 2018), in one ORS it is expected that AVs perform adequately, thus, without unexpected disengagement. The consistency in a road is evaluated over a homogeneous road segment. However, it cannot be measured directly. Previous studies propose various surrogate criteria, including operating speed or alignment indices to evaluate the geometric design consistency (Ng and Sayed, 2004).

Despite previous work, there is still a lack of empirical research connecting measurable geometric indices with AV system engagement under real-world conditions. Moreover, there is no available tool that road administrations can use to predict where partial automation will fail due to infrastructure limitations. While previous studies have explored curvature-related limitations of driving automation through simulation-based approaches or controlled experiments, typically focused on interstates, freeways, or standardized driving environments (Hu et al., 2022; Pappalardo et al., 2022), empirical evidence of automated driving system disengagements under real-world two-lane rural road conditions remains scarce. To the authors' knowledge, this study provides one of the first on-road datasets capturing SAE Level 2 disengagement events along operational rural road segments, directly linking these events to quantifiable geometric design consistency indices.

The relationship between alignment indices from the homogeneous road segments and the engagement status of the automated driving system was analyzed using Bayesian modelling. Unlike frequentist statistics, Bayesian statistics provides richer information by estimating the full posterior distribution of the parameters, rather than a single model point estimate with an approximate measure of uncertainty (typically represented by the standard error) (Bürkner, 2021). The model results provide insights into which variables have the greatest influence on autonomous driving system engagement, as well as the direction of this influence. Additionally, the predictive model helps identify actionable variables that can be targeted to improve rural road infrastructure and enhance traffic safety.

The geometric design of two-lane rural roads has been identified as a critical factor influencing AV performance. In this context, establishing measurable criteria is essential to guide road authorities in enhancing or adapting existing infrastructure to facilitate the safe operation of partially automated vehicles. The findings of this study provide an applicable methodology for assessing expected AV engagement performance on a given homogeneous road segment, helping translate the ODD framework into actionable planning and investment tools for infrastructure managers.

Accordingly, the objectives of this study are threefold: (i) to quantify, using real-world on-road disengagement data, how measurable geometric indices (e.g., CCR_{HRS}, radius, tangent length, and vertical curve parameters) influence SAE Level 2 engagement performance on two-lane rural roads; (ii) to develop a Bayesian predictive framework capable of identifying geometric thresholds associated with reduced operational reliability; and (iii) to translate these findings into actionable Operational Road Section (ORS) criteria that can support road administrations in AV-readiness assessment, infrastructure upgrading priorities, and the safe integration of partial automation into existing rural networks.

2. Methodology

This research was conducted in four stages: (i) Recreation of road geometry using Autodesk Civil 3D software; (ii) HRS identification; (iii) Real-world data collection and filtering; and, (iv) Model development.

This study analyzed three two-lane rural roads in Valencia, Spain, segmented by traffic and geometric characteristics. Two SAE Level 2 vehicles were used to collect engagement data while traveling, and a Bayesian model assessed influencing factors.

2.1. Homogeneous road segments and alignment indices calculation

This study was conducted on three two-lane rural roads (CV-50, CV-35, and CV-345), located in the Valencia Province (Spain), covering a total length of 159 km.

According to official sources, the Annual Average Daily Traffic (AADT) for 2024 was 1307 vh/d for CV-345, ranged from 1249 to 3629 vh/d for CV-35, and varied between 1966 and 7736 vh/d for CV-50. The road markings and pavement conditions were generally in good condition.

Road geometry (horizontal and vertical alignment) was accurately recreated using Autodesk Civil 3D software to facilitate detailed geometric analysis. Horizontal and vertical geometric parameters were derived from the reconstructed longitudinal alignment using Autodesk Civil 3D and in accordance with the definitions specified in the Spanish geometric design standard Norma 3.1-IC Trazado (Ministerio de Fomento, 2016).

Using the Google Maps "Street View" tool, the characteristics of the cross-section and the road markings (type of road marking on the edge and center of the carriageway) were determined. All information was collected in a Road Geometry dataset. The rural roads considered in this study cover a sufficient total length and exhibit substantial variability in geometric characteristics (tangent lengths, horizontal curve radii, and vertical curve parameters), which ensures the representativeness of the obtained results.

As a previous step in defining the Homogeneous Road Segments (HRS), the roads were initially divided into 11 general stretches based on main intersections, similar AADT, and cross-sectional characteristics (Cafiso et al., 2010).

Each general road stretch was then further segmented according to its geometric characteristics using the German methodology (RAS-L, 1995), which involves analyzing the Curvature Change Rate (CCR). The Curvature Change Rate for each homogeneous road segment (CCR_{HRS}) is defined as the ratio of the sum of the absolute deflection angles ($|\gamma|$) to the length of the road segment (L), as shown in Equation (1).

$$CCR_{HRS} = \sum |\gamma_i| \Big/ L \ (\text{gon} / \text{km}) \tag{1}$$

Fig. 1 illustrates the final segmentation step for one of the stretches: a cumulative absolute deflection angle profile is plotted against the road station to visually differentiate HRS based on consistent CCR behavior. Horizontal alignment were characterized and classified according to the German HCM (Forschungsgesellschaft für Strassen und Verkehrswesen, 2015). Table 1 defines four horizontal alignment classes based on CCR (Curvature Change Rate).

After applying this methodology, a total of 33 homogeneous road segments were identified. The next step was to calculate various alignment indices, including: (i) the average radius (R_{av}), determined as the sum of all curve radii divided by the number of horizontal curves; (ii) the average tangent length (TL_{av}), calculated as the sum of the length of all tangents divided by the number of tangents; and (iii) the average K_v vertical parameter (K_{av}), obtained by summing all K_v values and dividing by the number of vertical curves.

Table 2 presents the main geometric characteristics of each homogeneous road segment (length, cumulative absolute deflection angle, and curvature change rate), along with the abovementioned alignment indices. Additionally, the posted speed limit (PSL) of each HRS was included.

2.2. Real-environment data collection using SAE level 2 vehicles

With the aim of knowing the state of engagement in real environments of the vehicles currently circulating on the two-lane rural roads, intensive data collection was carried out on the study roads. Two instrumented SAE Level 2 vehicles were used to evaluate the engagement state of the vehicles while traveling along the HRS. The vehicles employed were: (i) 2018 Audi Q2 (hereinafter AV1), and (ii) 2022 Volkswagen Tiguan (hereinafter AV2), both equipped with Advanced Driver Assistance Systems (ADAS) capable of controlling simultaneously both lateral and longitudinal movements, including Adaptive Cruise Control (ACC) and Lane-Centering Assist (LCA).

Although the selected vehicles were representative examples of commercially available SAE Level 2 systems, it is important to acknowledge certain limitations regarding hardware transparency. In general, specific information about the sensor suite integrated in production vehicles—such as the number, type, and specifications of cameras, radars, or ultrasonic devices—is not publicly disclosed by manufacturers. Moreover, identical or very similar sensor modules may be shared across different vehicle brands, often supplied by common Tier 1 manufacturers. However, even when sensor types are known, the critical factor lies in the proprietary algorithms that govern the data fusion and decision-making processes within each vehicle's ADAS architecture. These internal software routines, which are typically confidential and vary across brands and models, are what ultimately determine how the system responds to road stimuli—such as those encountered along horizontally curved road segments.

Given this lack of transparency and the competitive nature of the automotive market, it is not feasible to access detailed information on

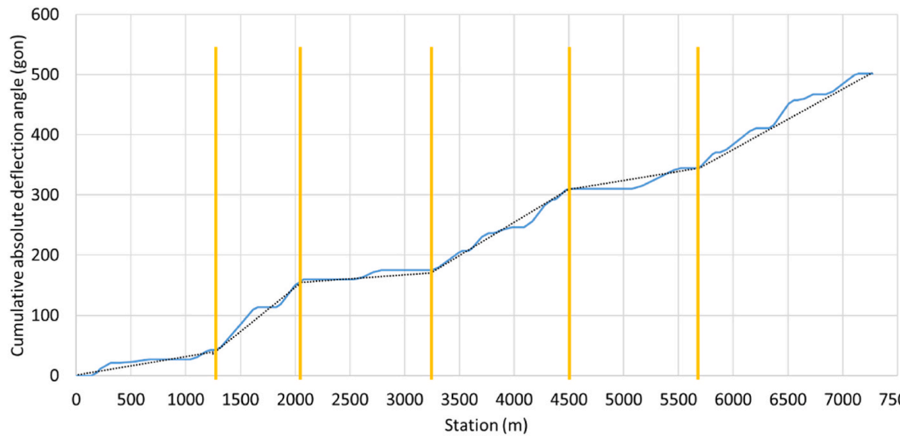


Fig. 1. Identification of homogeneous road segments (HRS) based on its CCR_{HRS}.

Table 1
Class of horizontal alignment depending on CCR, German HCM.

Class of horizontal alignment	1	2	3	4
CCR (gon/km)	0-50	50-100	100-150	>150
CCR (degrees/km)	0-45	45-90	90-135	>135

the inner functioning of these systems. Nonetheless, it is generally accepted that all SAE Level 2 systems aim to fulfill the same fundamental tasks: sustained lateral and longitudinal control under driver supervision. While the precise diversity of such systems across the vehicle fleet remains unknown, the use of two distinct commercial vehicles with different manufacturing years and models serves as a meaningful first step toward empirically understanding system engagement patterns in real-world conditions.

The automated driving system operates in one of two states: engaged or disengaged, as illustrated in Fig. 2. For the system to remain engaged, a minimum speed of 65 km/h must be maintained, and the AV must accurately detect road markings. The system disengages when it cannot ensure safe operation or when the driver assumes manual control to mitigate imminent risks. The objective of collecting real-environment data was to determine the percentage of the length of each HRS in which the AVs operated in an engaged state. This was accomplished by identifying the points where the automated driving system's status changed, using controlled experimental test drives with instrumented AVs.

Vehicles were equipped with two video cameras that integrated a GPS to register the travel, capturing both the automated driving system's status at each point and the vehicle's location. During the data

Table 2
Geometric characteristics and alignment indices of each homogeneous road segment (HRS).

HRS	L (m)	$\sum \lvert\gamma_i\rvert$ (gon)	CCR_{HRS} (gon/km)	R_{av} (m)	TL_{av} (m)	K_{av} (m/%)	PSL (km/h)
RS1	5500	126.53	23.01	1528.44	345.40	135.22	80
RS2	4193	237.57	56.66	656.92	113.13	89.55	70
RS3	1864	232.55	124.76	191.08	86.90	42.56	70
RS4	705	207.17	293.86	62.66	108.50	15.55	70
RS5	2758	175.64	63.68	219.02	279.50	63.38	70
RS6	1665	603.50	362.46	94.51	49.40	38.13	70
RS7	1781	261.31	146.72	194.59	73.64	32.43	70
RS8	3342	165.92	49.65	434.13	236.13	257.77	70
RS9	468	180.89	386.52	128.95	38.50	28.52	70
RS10	935	15.01	16.05	986.97	348.00	28.71	70
RS11	4399	191.00	43.42	1631.25	262.11	74.46	90
RS12	5722	180.37	31.52	2431.50	206.91	66.66	90
RS13	1272	42.39	33.33	949.67	156.25	93.00	90
RS14	802	116.93	145.80	283.00	169.00	59.46	90
RS15	1239	20.38	16.45	717.31	458.00	120.75	90
RS16	1188	130.69	110.00	419.49	53.50	56.38	90
RS17	1174	33.93	28.90	704.49	362.00	57.51	90
RS18	1598	157.38	98.48	441.64	83.00	71.50	90
RS19	765	26.17	34.20	300.00	322.00	19.379	70
RS20	3275	392.81	119.94	307.75	174.09	35.599	70
RS21	3647	669.07	183.46	444.21	70.20	35.66	70
RS22	635	139.10	219.05	199.50	49.50	93.58	70
RS23	4564	335.00	73.40	1209.62	84.21	57.38	70
RS24	1005	196.77	195.79	221.17	46.87	42.87	70
RS25	1308	541.05	413.64	137.36	24.09	29.68	70
RS26	1633	239.03	146.37	353.73	39.38	83.98	70
RS27	2687	55.46	20.64	1120.14	215.00	269.68	70
RS28	2679	372.71	139.12	190.60	97.00	32.20	70
RS29	1720	950.24	552.47	100.69	50.00	21.31	70
RS30	892	36.97	41.45	352.50	212.00	35.71	70
RS31	1985	398.80	200.91	133.75	122.00	28.75	70
RS32	2405	0.00	0.00	-	2405.00	54.21	90
RS33	9652	535.33	55.46	1080.25	120.31	69.54	70

Fig. 2. Data collection: (a) Vehicle instrumentation and (b) status of the automated driving system.

collection, vehicles were driving at the posted speed limit indicated at the beginning of each homogeneous road segment or at the generic speed limit for that type of road if the previous sign did not exist (see Table 1). This allowed for the identification of state transition points in the automated driving system (Fig. 2), which were synchronized with GPS-based road coordinates.

Video recordings were processed using Garmin VIRB Edit, which synchronizes video footage with embedded GPS time-stamps at a 10 Hz resolution, allowing engagement and disengagement transitions to be georeferenced along each route. Events were identified through manual review of the synchronized recordings based on the system status indicators and coded into two discrete states: (i) engaged and (ii) disengaged. The resulting automated driving system status dataset was then aligned with the geometric road database developed in Autodesk Civil 3D, enabling disengagement locations to be mapped onto homogeneous road segments with meter-level spatial accuracy. A consistent coding protocol was applied across all runs to minimize potential classification errors.

Both AVs were driven by the same driver, who has five years of experience with SAE Level 2 AVs, in order to ensure consistency across all runs and reduce inter-driver variability in the data collection process. Importantly, the driver had no influence over the disengagement events, as all disengagements were system-initiated and occurred while the automated driving system was actively engaged. The driver's role was limited to supervising the system and taking manual control only after disengagement occurred. Data collection was conducted in July 2023 and February 2024 during mid-morning hours to minimize the impact of traffic, avoiding its potential influence on recorded disengagements. The pavement condition and road markings were generally good. However, disengagement points were reviewed, and cases suspected of being caused by poor road markings were excluded from the analysis.

2.3. Automated driving performance

To evaluate the status of the automated driving system and the geometric characteristics of each homogeneous road segment, the percentage engagement (*PEng*) of the automated driving system for each road segment was calculated, as shown in Equation (2).

$$PEng = \sum L_{engaged} \Big/ L \tag{2}$$

where: $L_{engaged}$ is the sum of homogeneous road segment lengths during which the system remains engaged, and L is the total length of the homogeneous road segment.

This calculation was performed for each AV and each travel direction, obtaining four datasets per homogeneous road segment.

Subsequently, the engagement percentage was plotted against each alignment index for analysis. As a previous step to perform the Bayesian predictive model, a correlation analysis was developed to assess whether a significant relationship exists between the system's engagement status and each alignment index, or between the different alignment indices.

2.4. Bayesian model for automated driving performance

A Bayesian regression model was used to estimate the percentage of autonomous driving system engagement (*PEng*) considering various independent variables, such as alignment indices of the homogeneous road segments (HRS). The model was fitted using R software and the *brms* package for Bayesian multilevel modeling (version 2.22.0). The *brms* package offers a comprehensive set of post-processing and visualization functions, including posterior predictive checks, leave-one-out cross-validation, visualization of estimated effects, and predictions for new data (Bürkner, 2018, 2021).

To model the percentage of autonomous driving system engagement on rural road segments, a Zero-One-Inflated Beta (ZOIB) regression model within a Bayesian framework was used. The ZOIB model is particularly well-suited for the PEng variable, as it captures the continuous nature of percentage data bounded between 0 and 1 through a Beta distribution, while simultaneously accounting for the presence of excess zeros and ones (Liu and Eugenio, 2018; Ospina and Ferrari, 2012). This feature is crucial as certain road segments may exhibit complete disengagement (PEng = 0) or full engagement (PEng = 1) due to infrastructure limitations or optimal driving conditions for autonomous driving systems.

The model specification can be described as follows:

$$PEng_i \sim ZOIB(\mu_i, \varphi_i, \alpha_i, \gamma_i) \tag{4}$$

Where.

- μ_i represents the mean of the Beta distribution for values in the interval $(0,1)$.
- φ_i is the precision parameter of the Beta distribution for values in the interval $(0,1)$.
- α_i (Zero-One Inflation, ZOI) denotes the probability that the response variable takes extreme values (0 or 1).
- γ_i (Conditional One Inflation, COI) represents the probability that the response variable equals 1, given that it falls within the excess probability defined by α_i.

The link function used for μ_i, α_i, and γ_i is logit, while for φ_i is log.

The models were fitted using four Markov Chain Monte Carlo (MCMC) chains, each consisting of 2000 iterations. The initial 1000 iterations of each chain were designated as warm-up for sample calibration and subsequently discarded, resulting in a total of 4000 posterior samples for inference. Weakly informative prior distributions were assigned to the model parameters to regularize estimates and promote convergence (Bürkner, 2018). Following the brms package defaults, regression coefficients for all predictors and distributional parameters were assigned flat priors, while intercepts used weakly informative Student-t or logistic priors as appropriate.

Model predictive performance was evaluated using Bayesian R^2, as proposed by Gelman et al. (2018). From a Bayesian perspective, Bayesian R^2 provides an interpretable measure of the proportion of variance explained by the model for new data.

To further validate model performance, a 10-fold cross-validation procedure was applied. The dataset was randomly partitioned into ten equally sized folds, with the model refitted ten times. In each iteration, nine folds were used for model training, while the remaining fold served as the validation set for out-of-sample prediction.

The fitted model identifies the variables with the greatest influence on *PEng*, as well as the direction of this influence. Furthermore, the model can make predictions, allowing the estimation of *PEng* in other homogeneous rural road segments (HRS).

3. Results

3.1. Descriptive analysis

Two AVs were driven across the 33 homogeneous road segments in both travel directions having a total of 132 engagement percentage data (*PEng*). Two data were discarded due to failures in the data collection system, resulting in 130 valid observations.

Given that two different AVs were used to collect the data, first, a Kruskal-Wallis test was conducted to compare the median *PEng* for each vehicle, revealing no statistically significant differences between the performance of both vehicles ($E = 0.08$, $p\text{-}value = 0.777$). Additionally, a Kruskal-Wallis test was performed to compare the *PEng* medians based on the direction of travel along the segments. The results also showed no statistically significant differences ($E = 0.36$, $p\text{-}value = 0.546$). Therefore, all observed data were jointly analyzed within the same model.

Fig. 3 presents the histogram and density function of the response variable (*PEng*). The data distribution indicates that most values are concentrated at a *PEng* above 0.9, suggesting that the AVs engaged correctly on the majority of the homogeneous road segments.

Fig. 4 illustrates the relationship between the response variable *PEng* and the independent variables considered in this study. These graphs confirm that both AVs exhibit similar results. Additionally, clear variable relationships can be observed: higher CCR_{HRS} is associated with lower *PEng*. Some relationships show more uncertainty, such as *PEng* increasing with higher R_{av} and TL_{av}. Meanwhile, less evident relationships are observed in the graphs for *PSL* and Kv_{av}.

The correlation matrix between all the variables was computed, and the results indicated a correlation between the posted speed limit (*PLS*) of each homogeneous road and its geometric characteristics, since more favorable segments presented higher *PSL*. Therefore, *PSL* was also excluded from the model.

3.2. Bayesian Model for automated driving performance

A Bayesian predictive model for *Peng* was fitted. The independent variables considered in the model were: (i) CCR_{HRS}, (ii) R_{av}, (iii) TL_{av}, and (iv) Kv_{av}. All independent variables were standardized to improve model stability.

The regression coefficients of the fitted model and the Bayesian R^2 parameter distribution are presented in Table 2.

The *Rhat* values in the fitted model were 1 for all parameters, indicating that all chains converged properly and showed effective sample size measures (Bürkner, 2021). The 10-fold cross-validation indicates good model fit and robust predictive performance (mean elpd_kfold = 9.4, SE = 12.0; kfoldic = −18.8, SE = 24.0).

Additionally, the distribution of the Bayesian R^2 parameter suggests that the fitted model has a strong explanatory capacity. According to Gelman et al. (2018), Bayesian R^2 represents the proportion of variance explained by the model, considering both the predicted and residual variance. In this case, the mean Bayesian R^2 is 0.83, with a 95% credible interval ranging from 0.81 to 0.85. The narrow credible interval reflects low uncertainty around the estimate, reinforcing the model's reliability in capturing the underlying factors influencing autonomous system engagement on rural road segments.

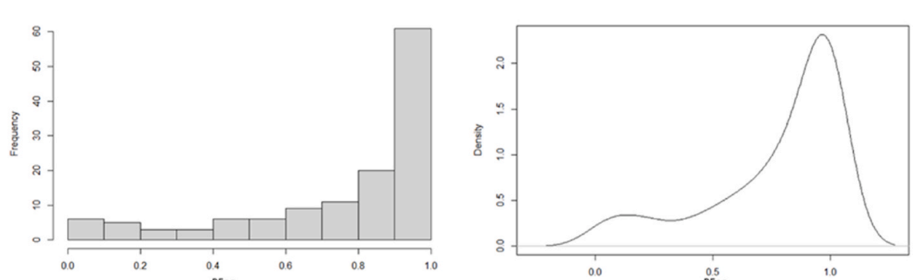
The values reported in Table 2 for model regression coefficients correspond to the standardized and transformed variables; however, these coefficients indicate both the direction and magnitude of influence that each independent variable has on the dependent variable.

The primary variable affecting engagement percentage (*PEng*) is CCR_{HRS}, which has a strong negative effect, meaning that higher CCR_{HRS} results in a lower *PEng*. The variables R_{av}, TL_{av}, and Kv_{av} have a moderate positive effect, implying that as they increase, *PEng* also increases. However, their confidence intervals include zero, indicating uncertainty and a weak or inconclusive effect.

Regarding the parameter coefficients (see Table 3), $\beta_{\varphi 0}$ has a positive value, indicating low variability in the response variable within the Beta component. $\beta_{\alpha 0}$ exhibits a negative effect on the response variable, indicating a higher probability that *PEng* takes extreme values (0 or 1). Conversely, $\beta_{\gamma 0}$ has a positive effect, implying an increased probability that *PEng* equals 1 in cases where extreme values occur, likely reflecting optimal conditions for sustained system engagement.

Fig. 5b displays the error of the predictive model's estimation. The results indicate that extreme values exhibit lower error, whereas response values between 0.4 and 0.8 show greater uncertainty in prediction, as it was expected.

Based on the model results, the variable CCR_{HRS} has the greastest influence on the variable response *PEng*. To better interpret this relationship, the conditional effect of CCR_{HRS} on *PEng* was calculated, showing the 95% credible intervals and providing a probabilistic prediction, thereby ensuring greater robustness of the results for planning applications. Fig. 5a illustrates this relationship expressed in real units, considering the remaining independent variables at their mean values. A clear negative relationship is observed, where an increase in CCR_{HRS} leads to a decrease in *PEng*. The relationship follows an accelerating decline, with high engagement percentages (above 90%) for low CCR_{HRS} values (below 100 gon/km). Conversely, when CCR exceeds 400 gon/km, the median engagement percentage drops below 25%, with the 95% credible intervals ranging from 13% to 37%.



(a) (b)

Fig. 3. Percentage of engagement (PEng) data: histogram (a) and density plot (b).

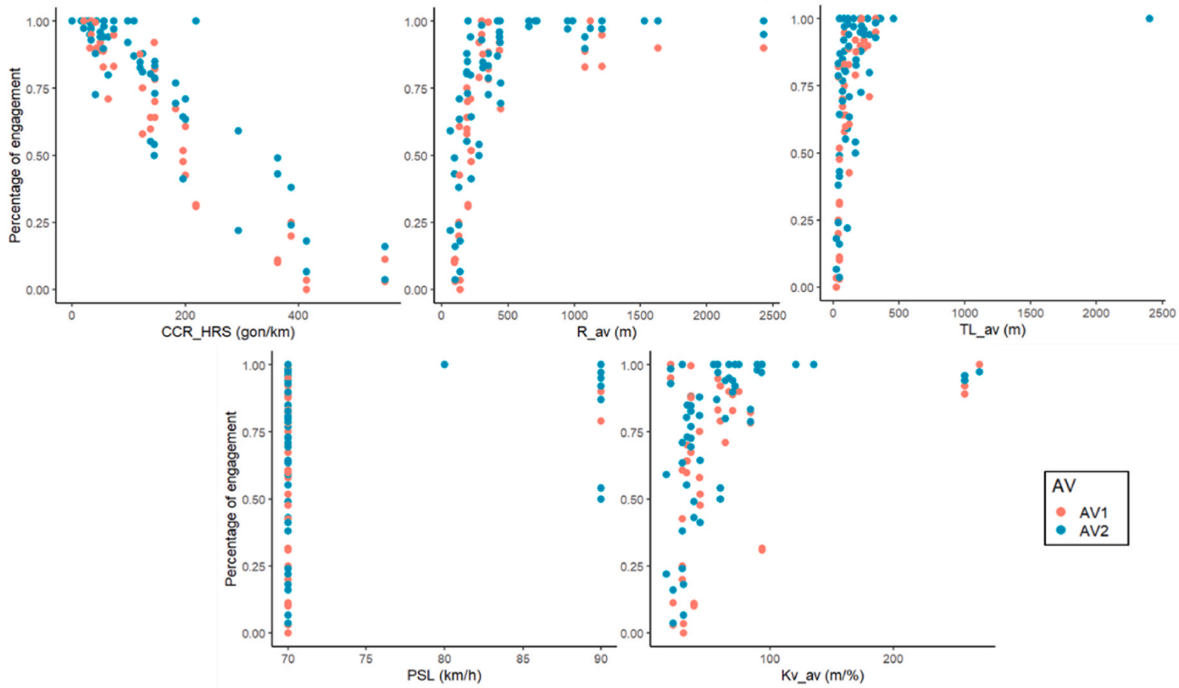


Fig. 4. Relation graphs including the main independent variables and the response variable.

Table 3
Parameter distributions of the model for PEng. Mean, standard error (SE) and lower and upper values of the 95% credible interval (l-95% CI and u-95% CI, respectively), reported for each parameter. Bayesian R^2 distribution is also shown.

	Mean	SE	l-95% CI	u-95% CI
Bayesian R^2	0.83	0.01	0.81	0.85
Parameters				
β_0	1.41	0.17	1.08	1.75
$\beta_{\varphi0}$	2.57	0.17	2.21	2.88
$\beta_{\alpha0}$	−1.26	0.29	−1.85	−0.72
$\beta_{\gamma0}$	3.68	1.50	1.47	7.33
$\beta_{scaleCCR\_hrs}$	−1.17	0.13	−1.42	−0.92
β_{scaleR_av}	0.23	0.15	−0.03	0.53
$\beta_{scaleTL\_av}$	0.55	0.51	−0.41	1.59
$\beta_{scaleKv\_av}$	0.03	0.10	−0.14	0.23

4. Discussion

Evaluating the performance of AVs in a real environment, at the level of HRS, is crucial for developing the concept of an Operational Road Section (ORS) previously defined by García et al. (2023). The developed study allows to identify, based on geometric variables, how current AVs operate on two-lane rural roads, and by applying the fitted predictive model, it is possible to know how they behave in other road segments. Particularly, the Bayesian Model obtained in this study demonstrates that geometric indices extracted from the HRS significantly influence the engagement percentage of AVs.

The model indicates that Curvature Change Rate of the homogeneous road segment (CCR_{HRS}) is the variable with the most noticeable effect on *PEng*, such that higher CCR_{HRS} corresponds to lower *PEng*. The fitted model allows for the prediction of the engagement percentage of current AVs on rural road segments based on their geometric characteristics. This model can serve as a practical tool for road administrations and transport planning specialists to identify segments of the network where partial automation is likely to operate reliably, and where targeted improvements may be needed. Thus, the applicability of this model can enhance road safety by reducing crashes caused by unexpected disengagements of autonomous driving systems, creating more confidence between drives and increasing the use of this system. As indicated by Nordhoff (2024), drivers decided to deactivate the automation system in anticipation of automation failure in environments exceeding the automation capabilities or when the automation exhibits unnatural or

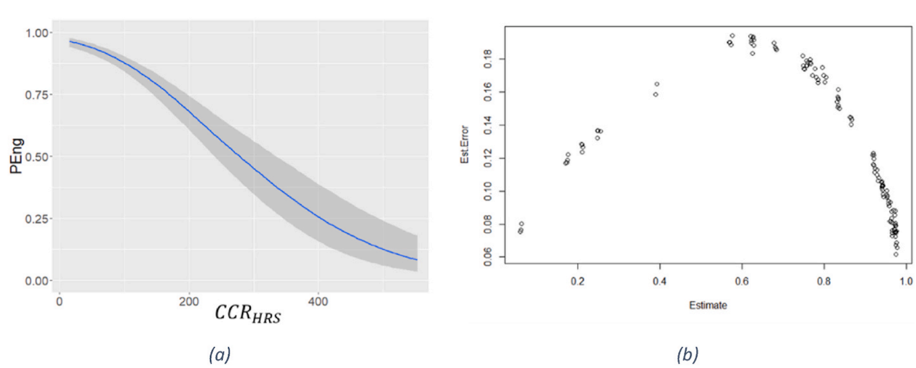


Fig. 5. Peng model results: (a) conditional effect of CCR_{HRS} and (b) estimated error prediction.

unwanted behavior.

The autonomous vehicles used in this experiment are SAE Level 2. As indicated by the results, both vehicles are based on similar technologies; however, AV2 is a more recent model with slightly more advanced technology, which adapts the vehicle's speed when approaching areas with unfavorable geometry. Although the overall engagement percentage values for both vehicles did not show statistically significant differences, it can be observed in Fig. 4 that AV2, exhibits slightly higher engagement percentage values at higher CCR_{HRS} (starting from around 300 gon/km). However, this observation should be interpreted with caution, as only two SAE Level 2 vehicle models were evaluated. The difference may reflect vehicle-specific software implementation or calibration rather than a generalizable technological trend. Therefore, broader conclusions regarding the effect of technological maturity on disengagement performance under complex geometric conditions require further investigation with a larger sample of AV manufacturers.

This study was conducted using two commercially available SAE Level 2 vehicles that are representative of current partial-automation systems operating on Spanish roads. Therefore, the findings provide insight into the present-day interaction between rural road geometry and Level 2 engagement performance. However, caution is required when extrapolating these results to other vehicle manufacturers or higher levels of automation. Future work should expand the vehicle sample and examine whether similar disengagement patterns occur in emerging SAE Level 3 systems under real-world rural road conditions. In the context of infrastructure planning, these results highlight the importance of developing data-driven criteria to assess road readiness for automated vehicle deployment. Road Administrations need tools that allow them to take measures at the places on the road where they are needed. In this context, they need to be able to directly identify those points of the road network where partially automated vehicles have difficulties operating in an autonomous way. This research advances in this line, based on the developed model, as there are HRS where the engagement percentage of AVs is very high. These HRS are associated with CCR_{HRS} values below 100 gon/km. Considering that an Operational Road Segment (ORS) is a road segment compatible with the ODD of most automated vehicles, given the results obtained, road segments with low CCR_{HRS} (less than 100) would be compatible for automated circulation and without disengagement events related to geometric design conditions. This can inform future infrastructure investment strategies by identifying which segments are already AV-ready, and which require design adaptations. Therefore, in these segments, crashes related to AV disengagements are expected to be minimal, as these areas exhibit favorable geometric characteristics that enable AVs to reliably detect road markings and curvature, and operate in an autonomous driving mode without difficulty.

Road segments with greater geometric variability pose greater safety risk, increasing the likelihood of crashes (Llopis-Castelló et al., 2018). These challenging segments also tend to hinder the operation of SAE Level 2 vehicles, leading to disengagements that may not be appropriately handled by drivers. Under these conditions, the issue of road safety is exacerbated, as drivers may fail to respond adequately to system disengagements while driving along less safe road segments. On the analyzed roads, the geometry variability has been measured with geometric indices extracted from the HRS. As can be seen in Fig. 5, results have shown that there are also homogeneous road segments associated with CCR_{HRS} values greater than 250 gon/km, leading to a low engagement percentage of the autonomous driving system, below 50%. In these segments, drivers have little trust in the autonomous driving system and should take manual control of the vehicle to prevent crashes. Additionally, specific signaling or real-time notifications over the reliably of operation can be implemented indicating whether automated driving is feasible on a given segment. However, the practical deployment of such interventions would require dedicated feasibility assessments, including cost considerations, regulatory alignment, and the development of standardized communication frameworks between automated vehicles and infrastructure operators prior to large-scale implementation.

These findings emphasize the need to consider road safety when designing infrastructures compatible with automated vehicle operation, ensuring that risks are minimized when human drivers interact with automated systems on complex geometric road segments.

In terms of accident risk, the central CCR_{HRS} range in Fig. 5, between 100 and 250 gon/km, is the most hazardous, as drivers may not anticipate disengagements. Within this CCR range, the probability of the AV operating with the automated driving system engaged is between 60% and 90%. As a result, drivers trust the automated driving system, and disengagements are unexpected, leading to less secure driver takeovers. It is within this CCR_{HRS} range that Road Administrations can intervene by implementing improvements to reduce disengagement, thereby reducing the risk of crashes and enhancing road safety. Interventions could range from geometric redesigns to improved signage and marking strategies, with prioritization based on model outputs. As Mueller et al. (2020) highlighted, with the use of partial-automation there are still some safety-related issues with AVs, including vehicle disengagement and AV-related crashes. DeGuzman et al. (2021) also indicated that disengagements are a critical issue that must be addressed to mitigate the risk of AV crashes, then actions focused on reducing disengagement will improve road safety on rural roads.

Both the current level of driving automation as well as higher levels would significantly benefit from certain improvements in road infrastructure, which would optimize automation capabilities and enhance overall road mobility (García et al., 2021). These improvements could involve construction-related actions, such as increasing curve radii in certain cases. Indeed, previous studies have shown that automated systems have limited operational capabilities on specific curves (Hu et al., 2022).

The operability of partial-automated vehicles is mainly based on the road markings of the road, which are used by the system for guidance and maintenance of the vehicle in the lane (Austroads, 2020). Automatic guidance through edge road markings becomes more complicated for higher curvatures. Previous researchers have focused on proposing methodologies or algorithms to solve the problem in the identification of lane edge road markings (Cácere Hernández et al., 2017), although solving this problem requires taking into account also the physical infrastructure (Pike et al., 2018). The results of this study align with Tengilimoglu et al. (2023b), who, based on an expert survey, concluded that road infrastructure certification or assessment is crucial for identifying suitable routes and ensuring road user safety during the early deployment of AVs. They also emphasized the need for specific roadway policies until the technology can be safely applied across all environments. Then, more cost-effective actions to implement on HRS with limited operation can require reinforcing horizontal road markings with vertical markings to enhance the AVs' ability to read the markings. In this sense, the model provides evidence-based thresholds that road agencies can use to prioritize low-cost interventions such as enhanced lane markings or signage where geometry adaptation is not feasible.

5. Conclusions

The performance of partial-automated vehicles in a real environment of homogeneous two-lane rural road segments (HRS) was evaluated. These HRSs were characterized by means of several geometric layout indexes (Curvature Change Rate (CCR_{HRS}), average radius, tangent length, and average parameter of vertical curves), which allow representing the geometric variability of the sections. Two types of SAE Level 2 vehicles were used in the experimentation. The vehicles were instrumented to record the system disengagement while traveling along the segments. The relationship between disengagement and geometric indices was analyzed by developing a Bayesian predictive model.

The model revealed that Curvature Change Rate (CCR_{HRS}) is the primary factor affecting the percentage of engagement. Thus, segments with significant curvature variations are less favorable for AV operation, whereas sections with more uniform and gradual horizontal and vertical alignments contribute to a more stable performance of automated systems. This study establishes specific geometric criteria that can be used to determine ORS on rural roads. The definition of ORSs could help establish levels of service for AV driving systems along road segments, supporting consistent and safe AV performance and building confidence in these technologies.

Additionally, the fitted model allows for predicting the engagement rate of current AVs on rural road segments based on their geometric characteristics. These predictions can assist road administrations in identifying road sections that are suitable for AV deployment, as well as those requiring design or operational improvements. Thus, the applicability of this model can improve road safety by reducing crashes caused by unexpected disengagements of autonomous driving systems. Moreover, it provides an evidence-based approach to integrating AV readiness into infrastructure planning and investment decisions. These findings represent a crucial step toward integrating automated vehicles into the transportation system, contributing to safer and more efficient road networks.

This study provides novel empirical evidence on SAE Level 2 disengagement behaviour under real-world operation on two-lane rural roads, an environment that remains underrepresented in current AV research. Methodologically, the work combines detailed geometric reconstruction of homogeneous road segments with a Bayesian zero-one inflated beta (ZOIB) modelling framework, enabling robust quantification of how design consistency affects engagement performance. The identified CCR_{HRS} thresholds offer actionable guidance for AV-ready infrastructure planning by road administrations. Furthermore, the inclusion of two commercially available AV manufacturers strengthens the robustness of the observed patterns, while the high Bayesian R^2 highlights the predictive reliability of the proposed model as a decision-support tool.

The main limitations of this study are related to the AVs used and the road segments included. Two currently available AVs were used, which are considered representative of the current fleet of vehicles on Spanish roads. However, it is anticipated that the constant evolution of technology will result in higher engagement percentages of the autonomous driving system with new AV models in the coming years. At the same time, it should be noted that SAE Level 2 systems exhibit substantial variability across manufacturers, particularly in terms of sensor configurations or perception algorithms. These technological differences may interact with geometric complexity in distinct ways, meaning that broader multi-platform studies are needed before generalizing the present findings to the entire Level 2 vehicle fleet.

On the other hand, the road segments considered in this study represent a high variability in CCR_{HRS}; however, the sample was predominantly composed of CCR_{HRS} values lower than 200 gon/km. Therefore, as further research, it is proposed to expand the samples of AVs and road segments, covering a higher range of CCR_{HRS}, in order to achieve a more accurate model and provide greater applicability.

Future data collection should prioritize (i) rural segments with extreme curvature indices, (ii) additional geometric consistency parameters combining horizontal and vertical alignment, and (iii) environmental conditions such as rain, low visibility, and degraded pavement markings, which are expected to further constrain AV engagement performance.

In addition, all experimental runs were conducted with a single driver to ensure consistency across tests and minimize inter-driver variability. Although all disengagements were system-initiated, future studies should incorporate multi-driver experiments to further assess potential behavioural influences during transitions of control.

Finally, expanding this framework into a reproducible AV-readiness roadmap will require integrating larger multi-vehicle datasets, independent test corridors, and standardized operational benchmarks, enabling infrastructure managers to apply the proposed model within scalable decision-support tools at network level.

CRediT authorship contribution statement

Griselda López: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Writing – original draft. **Sara Moll:** Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft. **David Llopis-Castelló:** Data curation, Formal analysis, Investigation, Methodology, Writing – review & editing. **Alfredo García:** Investigation, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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