Can AI Route You to Happiness? A Technical Study on Affective Automotive Navigation Interfaces

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Figure 1: We present HappyRouting, a new navigation system that routes after positive emotions. The two fast and happy routes are exemplary and exhibit different environmental characteristics that can influence a driver's emotions. We predict emotional weights for every road coordinate based on environmental, personal, and dynamic road context and find the optimal driving trajectory.

Abstract

Conventional navigation systems, fixated on metrics such as time and distance, neglect the driver's emotional well-being, despite driving routes being inherent emotional triggers. This raises a critical question for the Intelligent User Interface community: How can intelligent systems successfully route information based on emotion? To address this gap, we introduce HappyRouting, an empathic car interface designed as an initial attempt to guide drivers through real-world traffic while actively optimizing for positive emotional states. Our core technical contribution is a machine learning-based emotion map layer that predicts the affective valence along various routes using both static and dynamic contextual data. HappyRouting enables the generation of "happy routes" integrated into a functional vehicular interface prototype. We explored the efficacy of this approach in a preliminary, small-scale driving study ($N = 13$). Our initial findings provide provocative evidence: Emotion-optimized routes successfully increased the subjectively perceived valence by 11% ($p = .007$) compared to standard routes.

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Furthermore, despite taking 1.25 times longer on average, participants consistently perceived the travel duration as shorter. This result suggests that integrating emotional optimization could fundamentally challenge the speed-first paradigm. However, recognizing the constraints of our initial, limited sample, we conclude by discussing ethical and computational challenges that must be resolved before emotion-based routing can be safely and scalably integrated into next-generation intelligent navigation apps.

CCS Concepts

• **Human-centered computing** → *Interactive systems and tools*; *HCI theory, concepts and models*; • **Computing methodologies** → *Machine learning*.

Keywords

Empathic Interfaces, Affective Computing, Navigation, Machine Learning, Contextual-Aware Computing

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1 Introduction

Emotions play an important role in driving [37], as certain positive or negative arousal and valence states can lead to more thoughtful decisions during the driving process, resulting in safer driving. Today's car navigation systems enable users to navigate according to various objectives, such as the fastest route [34] or the shortest distance [34], or routes that require the lowest energy consumption [83]. In contrast to these routing modalities, we investigate a new objective by optimizing routes for positive emotions. Exaggerated states such as anger can significantly increase the driver's willingness to take risks and thus endanger the safety of all road users [25, 62]. Those exaggerated states lead to more traffic accidents [78]. Subsequently, we propose HappyRouting, a system that navigates drivers through routes that elicit positive (i.e., happy) emotions to improve the driving experience and safety. HappyRouting refers to routing mechanisms that optimize for the user's emotional well-being alongside conventional objectives such as travel time and distance.

While the vision, preferences, and design of empathic navigation have been presented in prior work [63], its technical concept, implementation, and concrete evaluation have rarely been the subject of research. In particular, the field of in-vehicle emotion assessment [10, 53] has evolved strongly over the past decade, while empathic real-world applications remain the exception [13, 86]. This disconnect between affective computing research and practical navigation applications represents a significant missed opportunity. While alternative approaches exist for influencing driver mood, such as in-vehicle ambient lighting, music, or interior design, routing itself remains an underexplored intervention.

Based on an increasing number of available datasets that classify driver emotions based on driving context [3, 10, 53], we conceptualize and implement the missing building blocks for an end-to-end empathic navigation interface. This disconnect between affective computing research and practical navigation applications represents a significant missed opportunity. While alternative approaches exist for influencing driver mood, such as in-vehicle ambient lighting, music, or biophilic interior design, routing itself remains an underexplored intervention.

Consequently, HappyRouting predicts possible emotions for thousands of unseen roads throughout a road graph and optimizes for the best tradeoff between positive emotions and travel time. While prior work has proposed emotion-focused navigation strategies based on static affective user ratings [43], our system is the first to integrate real-time contextual data for emotion-driven route adaptation. HappyRouting dynamically updates routes based on predicted happiness levels using remotely acquirable data sources without requiring subjective user reports after model training. Thus, our approach dynamically incorporates contextual road features to predict emotions in real-time. This enables personalized navigation that adapts automatically without requiring manual user input during or after model training. The goal of HappyRouting is to enhance emotional well-being by counteracting stress and frustration, known contributors to accident-prone behaviors [25, 62, 78].

Commercial navigation applications such as Google Maps and Apple Maps offer routes based on transportation modalities. HappyRouting advances beyond this by making emotional optimization explicit and measurable, grounded in a machine learning model. Closest to our work is SAR by Wang et al. [80], a route recommendation system that considers social and environmental context factors affecting human emotions. The authors developed a heuristic model that incorporates context information to determine the most enjoyable route. They evaluated their method based on computational performance and with the participation of five subjects in a driving simulator. To improve and extend this idea, HappyRouting incorporates a machine learning model trained and quantitatively evaluated on a large dataset. In contrast to a driving simulator, we conducted a real-world user driving study to investigate how HappyRouting affects emotions while driving. In this paper, we aim to ask the question: Can AI help us route emotions in automotive interfaces? And if so, what does a technical concept for that look like?

This paper presents design considerations, the resulting architecture, and an experienceable implementation for driving with positive emotions in real-world environments. We begin by discovering design considerations for a scalable affective navigation system applicable to unknown users, environments, and roads. We demonstrate that theoretical psychological assumptions hold for the experienceable system, showing for the first time a navigation system that regulates emotions positively by the choice of an optimized route. Based on this, we derive the technical architecture for HappyRouting. An in-the-wild driving pilot study with 13 participants investigates the effect on arousal and valence between choosing the *fastest* route and the predicted *happier* route. Crucially, this was a preliminary evaluation designed to cross-check the technical concept, not a comprehensive study intended to finalize the results on route-effect differences. Our study serves as an initial technical validation rather than a definitive evaluation, establishing feasibility before larger-scale investigations. Our results show a significant effect on perceived valence between the fast and happy routes, indicating that the happy route selected by HappyRouting improves valence. Furthermore, our participants were willing to use HappyRouting although positive routes consumed more time. Moreover, we conducted a simulation study across the entire region to compare the differences between the optimization objectives. Finally, we conclude our work by discussing ethics, the applicability of HappyRouting for other transport modalities, generalization for unseen roads, limitations, and future work.

Contribution Statement

The contribution of this work is threefold:

1. We present a set of comprehensive design considerations for a scalable affective navigation system that applies to previously unknown users and unseen environments.
2. With HappyRouting, we demonstrate that guiding design decisions hold for an experienceable end-to-end system and show for the first time that navigation systems can regulate emotions positively by the choice of routes in a real-world setting.
3. We characterize the qualitative and quantitative properties of our proposed affective navigation system in a pilot, in-the-wild user study ($N = 13$) and with detailed simulations.

2 Related Work

HappyRouting's idea of routing after positive emotions build on concepts found in driver emotion assessment, contextual computing, and empathic car interfaces.

2.1 Inferring Driver Emotions

Using context-aware sensing [73] using human sensing in cars [44] gained increased attention to understanding driving behavior or facilitating novel perceptual car interfaces. In this context, empathic car interfaces benefit from understanding the driver's emotions to adapt their interface, contributing positively to the user's emotional state [76, 86]. Emotion assessment can be achieved through *direct* and *indirect* user observation.

Direct observation methods, such as recognizing facial expressions [26, 28], are a convenient method to infer emotions while driving. Although facial expressions are a commonly used modality [15], it remains controversial in research [40, 57]. Alternatively, emotions can be derived from psychophysiological signals such as electrodermal activity, heart rate, muscle tension, respiratory rate, and electroencephalography [3, 7, 75]. The setup of in-car physiological sensing is often problematic due to insufficient signal quality levels [24] and missing user acceptance [82].

Indirect user observation through analyzing contextual driving data gained increasing attention for emotion recognition. Zepf et al. [84] surveyed affective automotive user interfaces and identified several factors causing emotional triggers and changes, including driving behavior, music, and road conditions. This fact was exploited by Liu et al. by analyzing vehicle CAN-bus data [53], reaching subject-independent F1-scores of 59%. Bethge et al. [8, 10, 11] showed that contextual driving data captured with a smartphone resulted in subject-independent F1-scores of 56%, an improvement over using facial expressions as a baseline. In contrast to previous work [53], the authors utilized data from a smartphone only. To better represent such diverse data, Route2Vec [36] utilizes attention-based embeddings to compactly encode heterogeneous route contexts, a foundation that has been further extended by RouteLLM [35] to enable native reasoning over environmental factors within large language models.

An empathic navigation system imposes additional constraints on the observation method, as it is required to predict emotions on thousands of possible road segments to find the optimal emotion-aware route. Since, in most cases, there is no direct observation input (e.g., crowd-sourced facial expressions) accessible for every unseen road segment, algorithms trained on remotely accessible observations (e.g., traffic, road properties, or weather) are needed. Beyond computational sensing approaches, complementary strategies for influencing driver emotions exist. Biophilic design principles, which incorporate natural elements into vehicle interiors through materials, lighting, and visual motifs, offer low-complexity alternatives that do not require ML infrastructure or raise privacy concerns [17, 42, 81]. Similarly, adaptive ambient systems can modulate interior lighting and climate to support emotional regulation. While these approaches operate differently from route optimization, they represent part of a broader design space for affective automotive interfaces that future systems may integrate.

2.2 Affective Routing

Routing is considered a factor that strongly influences the driver's emotions. In their detailed study, Braun et al. [13] explored 20 concepts for empathic car interfaces, finding that empathic navigation is desired among drivers in Germany and China. In a web survey, Pfleging et al. [63] evaluated the general idea of experience-based navigation and identified the fastest route and the route with the least stress as the most important factors for route selection. At the same time, users often bypass the fastest route, for example, to avoid stressful situations and negative emotions [19]. Zepf et al. [84] demonstrated that most positive emotional triggers are closely tied to the environment. Accordingly, positive and negative experiences with a route play a crucial role in the acceptance of future route recommendations [72]. Previous work focused on various routing concepts that may indirectly influence emotion. This stands in contrast to HappyRouting, which directly optimizes for positive emotions by applying a diverse set of features.

Quercia et al. [66] investigated a scenic routing concept using crowd-sourced images associated with Points of Interest (POIs). Similarly, Runge et al. [70] identified scenic rides by applying a pre-trained neural network to street view imagery. The routing methodologies [66, 70] incorporate contextual routing concepts but are limited by crowd-sourced data and the visual attributes of the place itself. Wang et al. [80] presented a route recommendation system that optimises routes based on their social and emotional impact. The authors presented a heuristic model that determines a route based on factors such as traffic and the historical emotions associated with a previously driven route. The authors found that 4 out of 5 participants who participated in a simulator driving study preferred the route suggested by the algorithm to a randomly assigned route.

Huang et al. [43] presented a mobile application that uses an affect-space-model for collecting emotional responses - the basis for a route planning algorithm. A user study revealed that the generated routes are preferred over conventional shortest routes used in navigation systems.

Using physiological data, Tavakoli et al. [77] introduced a framework for routing recommendations based on the driver's heart rate collected in a three-month in-the-wild study. The authors note that the proposed framework can identify infrastructural elements in a route that may potentially impact a driver's well-being. Hernandez et al. [41] proposed the long-term vision of crowd-sourced driver stress detection [59] using "Empathetic GPS" - a vision of a navigation system that geographically identifies routes which minimize driver stress.

2.3 Summary

Previous works show that empathic navigation is a highly desired feature among drivers and co-drivers [13, 63] (see Table 1 for a summary). Our work leverages such initial concepts and contributes with the technical building blocks to ultimately present HappyRouting, a real-world, end-to-end affective navigation system. To our knowledge, HappyRouting is the first experienceable system that predicts emotions for real-time routing in-the-wild.

3 Design Considerations

The following section describes our design considerations for HappyRouting. We start by describing how HappyRouting will affect the driver's emotions, mood, and well-being. Then, we look into different routing concepts and conclude with relevant objectives and the modeling of driver routes. A particular focus on ethics and limitations can be found in our discussion in Section 7.

3.1 User Emotions, Mood & Wellbeing

Our goal was to create a joyful driving experience that is implicitly composed of contextual data such as traffic, road characteristics, and weather. In general, our approach can be considered a method for regulating emotions [55] during navigation, particularly aiming for an upregulation. Emotions can be regarded as situationally bound, limited in time, with either a positive or a negative state [55]. Hence, emotions can change throughout a ride. For example, the traffic flow or route characteristics, which are among the primary sources of information for HappyRouting, can manipulate perceived driver emotions.

In contrast to emotions, the user's mood is less intense and specific and often not caused by a particular event or situation [31], such as the current weather [49]. HappyRouting primarily aims to elicit positive emotions, eventually positively influencing the user's mood. However, this approach is deliberately oversimplified as it is necessary to consider the overall process of mood adjustment and counter-hedonistic effects [50]. This means that positive mood is not only established by a simple aggregation of positive emotions but rather a complex interplay of positive *and* negative emotions (e.g., people like to listen to sad music to adjust their mood positively) [58].

Another constraint of our approach is focusing on primary emotions, particularly positive affect. However, positive affect and the absence of negative affect represent only a subset of possible dimensions to improve subjective well-being [32]. Other important factors, particularly in the dimensions of social well-being and eudaimonic well-being (e.g., self-acceptance), are currently well outside our scope of work. In summary, HappyRouting can be seen as a first important step towards a more detailed understanding of how technical systems can positively impact emotions. On the other hand, the aforementioned limitations raise many important questions for future work.

3.2 Routing Concepts

All routing concepts share the commonality that they operate on a graph of nodes and edges with associated weights. Edges represent road segments in the road network, while nodes connect these segments. The weights associated with a road segment can represent different optimization objectives, for example, routes with the fine particulate (PM2.5) intake [54] or those requiring the least energy [83]. For most use cases, the primary optimization objective is closely tied to travel time and distance between the two nodes. Ultimately, this fact necessitates the need for multi-objective optimization, which can be achieved through single- and multi-stage optimization.

Single-stage optimization combines multiple optimization objectives into one optimization method. For this purpose, multiple weights corresponding to the different objectives are associated with each edge, also known as layers. In the simplest case, the final weight can be determined by weighted addition of the individual weights [79] or by introducing a penalty factor [47]. If multiple objectives have statistical dependencies, more complex models, such as Bayesian Belief Networks, can determine the combined weight [74].

Multi-Stage Optimization conducts multiple optimizations in succeeding steps, with the first steps representing the most important optimization objectives. This optimization procedure can be used if the optimization problem is expressed through multiple models, e.g., road graphs and lists of POIs. For example, Quercia et al. [66] apply Eppstein's algorithm [29] to find the N shortest paths, and then, in a second stage, rank those paths by user scores for POIs. A modified approach for the N shortest paths problem was presented in SAR [80].

For HappyRouting, we apply single-stage optimization, as we can associate emotions to each road segment, enabling us to express the problem in a uniform way. HappyRouting's primary objective is *travel time*, while emotions are added to the graph's weights as a penalty term [47]. The penalty term is computed using a machine-learning model that considers various emotion-related features. Routes can be computed with efficient graph-based algorithms like Dijkstra or A*, or in our case, the contraction hierarchies algorithm specifically designed for vehicle navigation optimization [33].

3.3 Optimization Objectives

Considering human wayfinding, Golledge [34] ranked various route selection criteria. *Shortest distance* ranked first and *least time* second, followed by *fewest turns* and *most scenic*. Less generic approaches

Table 1: Description of papers and their contribution to route recommendation after considering emotions. The dimension *Model Applicable to Unseen Environments* refers to the fact that the developed model, either heuristic or as a classifier, does not rely on crowd-sourced user data (e.g., POI ratings).

Paper	Emotion Classifier	Model Applicable to Unseen Environments	Routing Idea	Routing Algorithm	Routing Quantitative Simulation Study	Routing Simulator User Study	Routing In-the-Wild User Study
Bethge et al. [9, 10]	✔	✔	✖	✖	✖	✖	✖
Huang et al. [43]	✖	✖	✔	✔	✖	✔	✖
Liu et al. [53]	✔	✔	✔	✖	✖	✖	✖
Pfleging et al. [63]	✖	✖	✔	✖	✖	✖	✖
Wang et al. [80]	✖	✔	✔	✔	✖	✔	✖
HappyRouting (Ours)	✔	✔	✔	✔	✔	✖	✔

consider criteria like *least energy* [83], *least fine particulate (PM2.5) intake* [54], *optimal physical exercise* [74], or *personalized accessibility metrics* [48, 79]. We can categorize these criteria into the following optimization objectives:

- *Environment-dependent* objectives, e.g., *shortest distance* do not change over the duration of the trip. In HappyRouting, we utilize properties of the environment, like the number of lanes and speed limits, to derive emotions.
- *Time-dependent* objectives change over the duration of the trip, such as *least time* would be affected by time-dependent traffic. Our primary optimization objective in HappyRouting is the travel time, which is penalized by negative or neutral emotions.
- *User-dependent* objectives depend on personal criteria, such as accessibility needs. HappyRouting attempts to scale across various users, including unknown ones. Therefore, we include some user-dependent features, i.e., personal context as input in our architecture but identify a need for further exploration in future work.
- *State-dependent* objectives consider the state of an object, such as an electric vehicle's charging state [83]. We do not consider this in our objectives for practical reasons and generalization purposes.

In the future, we envision a multi-stage optimization navigation system using a breadth of such parameters to find the most user-optimal route. Different optimization objectives raise the question of their societal impact, particularly when applied at a large scale. Johnson et al. discuss such potentially negative influence of scenic routing algorithms and their optimization objectives on neighborhoods and parks [46]. The described optimization objective links directly to the features used in HappyRouting described in Table 2. Our system uses environment-dependent features such as road_type, max_speed, n_lanes, and satellite_greenness, which remain constant during a trip. Time-dependent features include traffic metrics (reduced_speed, freeflow_speed), weather conditions, and daytime. User-dependent features include age and before_emotion, enabling personalization. We refer to Section 4 for a detailed description of the used input features to estimate emotions and Section 7 for a more detailed discussion on societal impact.

3.4 Modeling and Simulation

Most sophisticated optimization objectives require an approach to express their influence on the weights of a graph.

The most common form is modeling based on historical observations, especially of travel times [64] or least fine particulate (PM2.5) intake [54]. However, the two examples differ greatly in how they can be applied to a graph network. Regarding travel times, observations can directly be linked to edges in the graph. For fine particulate (PM2.5), an intermediate interpolation and edge association step is needed, as observations are linked to measurement stations [54]. HappyRouting applies both methods for different features: On the one hand, the characteristics of the road segments are used as direct parameters, and on the other hand, metrics of the surrounding landscape, such as the green index, are interpolated.

Models that take travel time into account require time-dependent modeling, as traffic and, therefore, weights in the graph change over the duration of the trip. Such look-ahead models are often based on historical observations. Except for *travel time*, HappyRouting currently does not consider additional fast-changing environmental parameters. In particular, the weather will be considered static throughout the trip. This design choice reflects a lowered computational effort at the cost of potentially less accurate predictions in the future.

The penalty term for each road segment can be represented as a regression model in many use cases like travel time prediction [64]. In contrast, HappyRouting is based on a multi-class model for predicting emotions (e.g., happy, neutral, sad), where the inputs consist of road parameters and the outputs represent the pseudo-likelihood of each class. To synthesize the penalty term for the graph edges, we used only the pseudo-likelihood of the class *happy*. Alternative methods represent the model as a binary classifier (e.g., happy against all other classes) at the cost of decreased performance due to an increased imbalance of classes.

4 Architecture

In the following section, we describe the architecture of our system and the necessary steps to provide the user with an emotion-optimized route. We derive the technical considerations from the concept design considerations presented in Section 3.

4.1 Requirements

Finding an emotional-relevant route is complex due to several reasons. The route optimization must be executed in near real-time, and all information required for the routing algorithm must be

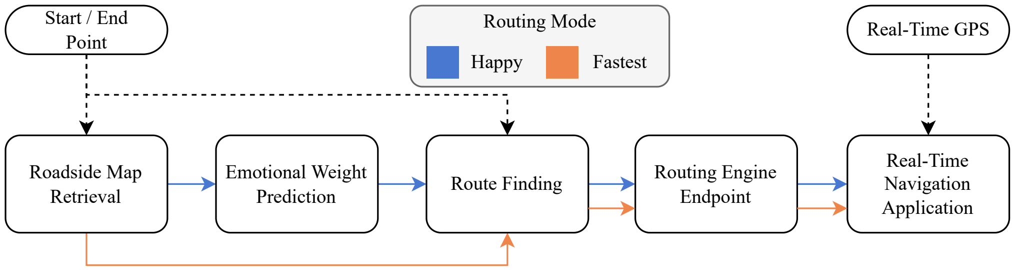

Figure 2: Architecture of happy navigation computation.

available (see Section 3). Given a user's starting point a and selected destination b as GPS coordinates, we search for a route that likely makes the user happy.

The following requirements must be fulfilled by HappyRouting:

Req 1: The emotional component of the route is subject to context, person, and traffic characteristics

Req 2: The happiness weight of road segments has to be assigned before starting the navigation

Req 3: The system should be usable like a common smartphone navigation system
  (a) The system should enable destination search functionality (e.g., finding a train station)
  (b) The system should re-locate given the smartphone's geolocation and show the trajectory of the happy route
  (c) The system should output turn-by-turn navigation instructions to the driver in real-time

Req 4: The navigation engine should be designed as a scalable system
  (a) Provide happy routes in every geolocation (no pre-annotated or historic routes)
  (b) Optimize the route trajectories without delay so that the user receives the route recommendation $< 2s$ after entering the destination

4.2 General Framework

Figure 2 provides an overview of the system architecture. Depending on the start to end point, a roadside map is created via OpenStreetMap (OSM)[1]. We then perform a custom map layer computation in the subsequent step in which we predict emotional weights for every edge in the road graph. The happy route is then found with the newly created map via an optimization procedure. We expose the endpoint of the navigation engine and build a real-time navigation smartphone app on the basis of the routing engine.

4.3 Input Features

We used a reduced number of contextual road features of the original dataset [10] for our custom context-emotion classifier model. The selected features were based on Braun et al. work [16] where driving behavior, traffic, vehicle performance, and environmental factors were found to be discriminative of emotions. We filtered the variables based on the following requirements: (1) real-time, on-device computation without accessing the vehicle itself, (2) no direct user interaction, (3) non-critical consumption of device resources, and (4) time-critical computability. We restricted the model to only those input features that can be pre-computed before driving (**Req 2**)[2]. Furthermore, personal factors such as age were used to adapt to user-dependent emotion-route preferences. The selected features are shown in Table 2.

We computed the weather and traffic features for every road segment using Microsoft Azure's Weather and Maps API. Although the weather often stays similar across a larger geographical area, we included weather in the emotion prediction as the weather condition affects the route choice of our algorithm. For example, in rain, users may favor broad streets, while sunny conditions may prompt a preference for curvy, narrow roads. Thus, the emotion classifier learns this input interdependence. The feel temperature was provided directly by the Azure Weather API and comprises the levels of humidity, light, wind speed and real temperature. The road type features were gathered from OSM by selecting the nearest OSM node with its corresponding parameters. Based on satellite imagery, we quantified the vegetation and determine the green index [20] at any given geolocation. To obtain the greenness, we computed the relative amount of pixels associated with vegetation in each given satellite image. We computed the curviness using a weighted measure of the length of curves, which depends on the radius of a circumscribed circle that passes through all three consecutive geocoordinates in a route. Given a, b, c as the length of the three sides of a triangle, the radius of the circumcircle is given by the formula:

$$r = \frac{abc}{\sqrt{(a+b+c)(b+c-a)(c+a-b)(a+b-c)}} \tag{1}$$

4.4 Emotion Prediction

The foundation for our emotional routing is a computational behavior model for predicting emotions using road context. We thereby learn subject-independent emotion labels for previously unseen road segments (**Req 4**). Recently, Bethge et al. [10] proposed an in-car remote-sensing system able to predict emotions on unknown roads for unknown users with very high confidence. The model is able to predict discrete emotion categories ('happy', 'sad', 'neutral', 'angry', 'contempt', 'disgust', 'fear', 'surprise') using contextual road information (**Req 1**). Although many affective representation models exist (e.g., Plutchik's wheel of emotions describing 56 emotions [65] or Russel's circumplex model [71]), we selected the seven

[1]https://www.openstreetmap.org

[2]Contextual variables such as the current acceleration cannot be pre-computed.

Table 2: List of available features to predict drivers' emotions.

Context	Feature	Example	Description	Source
weather	feeltemp_outside	13.0	temperature outside of car	Azure Weather
	windspeed	5.6	windspeed in km/h	
	cloud_coverage	76	relative cloud coverage in %	
	weather_term	'clear'	description of weather condition	
traffic	reducedspeed	7.295495	current reduced speed to freeflow speed	Azure Traffic
	freeflow_speed	115.0	freeflow speed expected under ideal conditions	
road	road_type	'residential'	road type of current position	OpenStreetMap
	max_speed	120.0	maximum allowed speed on the road	
	n_lanes	2	number of available lanes	
greeness	satellite_greeness	0.2	percentage of green pixels in the environment	Mapbox Satellite
time	daytime	'afternoon'	current daytime	system input
personal	age	21	age of the driver	user input
	before_emotion	'happiness'	subjective expressed emotion before driving	

emotion categories, as well as the category neutral. Our model is designed to predict multiple emotions to ensure adaptability for navigation use-cases where other emotion predictions are needed, rather than simplifying it to a binary classification setting for just predicting 'happiness'. For example, future research could use our classification model to build a navigation framework that avoids 'sad' emotional states for people with an anxiety disorder or emotional sensitivity [3]. The choice of our set of discrete emotions is practically grounded in Ekman's theory which is often associated with emotion detection by analyzing facial features. We utilize this well-known model for our optimization and establish a connection to previous work [22, 86].

In their in-the-wild driving study, the authors collected contextual driving data and subjective emotional states expressed by drivers while driving [10]. To avoid distracting the driver and biasing the ground-truth labeling, a beep tone was triggered every 60 seconds, prompting the driver to verbally express their emotion according to a predefined set. We acquired the dataset and extended it by another 14 participants to 26 participants in total, reflecting in 31 sessions consisting of 438 minutes of emotion-labeled driving and eight classes of emotions in total[4]. The dataset used in our study exhibits imbalanced labels due to the infrequent occurrence of negative emotional states in naturalistic driving environments. Specifically, our dataset includes approximately 120 minutes of driving data labeled with 'happy' emotional states. We describe detailed information about the classifier dataset and the labeling procedure in the Section A.

After defining the input features, we selected a Random Forest Ensemble Learning as classifier based on a 10-fold grid-search cross-validation (using Support Vector Machines, Feedforward Neural Network, Decision Tree, Adaboost, and Random Forest classifier from scikit-learn with hyperparameter optimized parameters) in which the Random Forest achieved the highest average F1 score. In the future, more complex input features and flexible model architectures such as deep neural networks might be employable to achieve an even better emotion prediction. For the data and input feature complexity, the Random Forest classifier achieved the best trade-off in terms of performance and variance. The prediction model [5] is tested via a leave-one-subject-out cross-validation on unseen participants. Within one cross-validation fold a Random Forest model is trained on 25 participants and the performance is tested on the left-out participant's emotional data. Thereby, we prevent overfitting on individual participants' emotional data and assess how well the model generalizes, i.e., in predicting the emotions of unseen participants. This evaluation allowed us to gauge the accuracy of a correct emotion prediction for a user that has yet to use the navigation system. The results are outlined in Table 3.

Overall, our model achieves a mean emotion recognition accuracy of 63% with a balanced F_1 score of 53%[6]. These results are slightly inferior to current subject-independent contextual emotion classifiers [10, 53], but are also based on a remotely acquirable, and thus much reduced, feature set. As a baseline in our dataset, we recorded a driver-facing camera stream and applied a FERPlus-trained classifier [5], showing that the collected contextual features still outperform facial expressions [10].

We also report the performance of a binary classification (happiness vs. non-happiness label prediction). Here, the results of our binary classification model are superior to the facial expression engine. Our model achieves a mean result with an accuracy of 65% and a F_1 score of 0.66 vs. the facial expression engine with an accuracy of 20% and a F_1 score of 0.12. The results of the facial expression engine are vastly inferior as happy emotions are nuanced facial expressions that are hard to detect with a non-participant-trained computer vision model. Therefore, we argue that successful prediction of happiness on the road may require a more nuanced and multidimensional approach that considers a range of subjective and objective factors, including individual differences, social context, and environmental factors (as we do in our model). While the F1 score may not seem optimal, it's essential to consider that classification takes place over numerous road segments, ranging from hundreds to thousands, on a given route. Despite performance

[3]We note that 'happiness' and 'sadness' are not antagonistic emotional states.
[4]We note that the sole purpose of the training dataset is to learn an emotion prediction engine that links contextual properties and emotion labels. Thus, this dataset differs from the in-the-wild experiment evaluation of HappyRouting.

[5]Model parameter: class_weight = 'balanced', max_features= log_2, n_estimators= 50.
[6]Neutral emotions represent the majority class of our dataset, while happy emotions are at 23%, being predicted second best (after neutral) in terms of precision and recall

Table 3: Mean (standard deviation) accuracy, class-weighted precision, recall, and F_1 scores of the cross-validation on unseen participants, i.e., leave-one-participant-out cross-validation. The model predicts eight emotion classes in total (left) or happiness vs. non-happiness emotions (right). We applied a FERPlus-trained classifier [5] to the dataset, confirming findings in [10].

	Leave-One-Participant-Out Cross-Validation (all emotion classes)				**Leave-One-Participant-Out Cross-Validation (happiness only)**			
Input	Accuracy	Precision	Recall	F_1	Accuracy	Precision	Recall	F_1
Facial Expr. (FERPlus [5])	.55 ± .18	**.53** ± .19	.55 ± .18	.49 ± .19	.20 ± .15	.20 ± .34	.09 ± .42	.12 ± .38
Our model	**.63** ± .16	.49 ± .21	**.63** ± .16	**.53** ± .20	**.65** ± .14	**.22** ± .20	**.75** ± .42	**.66** ± .10

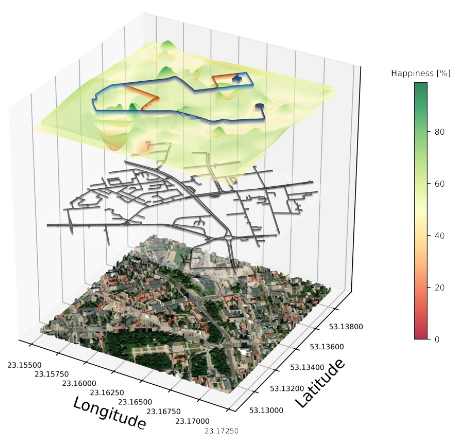

Figure 3: Graph Building for Happy Route Optimization. The navigation finds the optimal emotional path according to the emotion-road-weight regularization (Equation 2). The bottom layer is a satellite image. The layer above represents the routable roads. Above is an emotion heatmap based on interpolation of the computed happiness points. The red path is the fastest path offered by navigation, while the blue path is the happy path.

fluctuations for specific segments, the overall results will generally even out when applied to many instances. Our metrics align with findings in prior works, particularly when evaluated in a generalizable leave-one-subject-out setting, such as ours [10, 53].

4.5 Routing Map and Navigation

Having defined the predictive model required to simulate emotions based on contextual information collected remotely, we now present the system required to provide users with a route optimized for emotions. In Figure 3, we display how a happy path may differ from the fastest one based on a custom emotion map layer.

Routing Map Generation. We defined a custom emotion map layer that contains predicted emotions and optimizes the route thereafter. Given a road graph G with vertices V and edges E, we predicted emotion weights for every driveable segment E. We then applied the contraction hierarchies algorithm [33] to the road graph by optimizing for the following equation with the user's start point a and endpoint b:

$$route(a, b) = min \sum_{i,j \in [a,b]; i \neq j \in E} \frac{d(i, j)}{\lambda * e(i, j) * c(e(i, j))} \tag{2}$$

In contrast to the fastest route, our optimizer minimizes the sum of the travel time of each edge $d(i, j)$ and penalizes its decision by the happiness weighing factor λ and its corresponding predicted happiness value $e(i, j)$, multiplied by the confidence of the individual happiness prediction $c(e(i, j))$. Here, the last part ensures that it is favorable for the optimizer to choose edges with high predicted happiness values and lowest travel time[7]. Following the minimization optimization, if two edges yield equal emotional value, the one with the lowest travel time is selected. In our simulation study (see Section 6), we found that the happiness weighing factor of $\lambda = 20$ yields a good tradeoff between travel time and positive emotions.

Optimization Backend. To implement the optimization procedure, we used the open-source, Java-based framework GraphHopper[8]. GrapHopper offers a fast and memory-efficient routing engine, including a web frontend and a standalone web server to calculate a route's distance, time, turn-by-turn instructions, and trajectory properties. We adopted the routing optimization according to Equation 2. We did not employ a standard A* algorithm [38] for optimal route finding due to performance reasons. Instead, we disabled all initial edge weight calculations for happy routing and built a prominently-used CH (Contraction Hierarchy) graph [33] with precalculated happiness weights to speed up optimization (**Req 4**). We exposed a happy and fastest routing computation endpoint. The interactive GraphHopper routing endpoint for a happy route computation is shown in Figure 4. Commercial navigation systems such as Google Maps and Apple Maps would likely employ the same route estimation formula for the fastest route, although their exact computation method is unknown.

Smartphone Navigation App. We implemented a scalable mobile application to provide users with the ability to navigate. Therefore, we customized the Android application PocketMaps[9] to use our

[7]We opt the routing decision formula to be influenced by the predicted emotion value in the denominator as the travel times have no equal lengths and regularizing longer route segments (high $d(i, j)$) with the emotion scaling is more beneficial than, e.g., subtracting the emotion values.
[8]https://github.com/graphhopper/graphhopper
[9]https://github.com/junjunguo/PocketMaps

optimization engine (**Req 3**). Our mobile application tracks the current smartphone geolocation using GPS and is able to search for destinations on the map via Google Maps search. The application then performs map matching of the current geocoordinate to the road segment and outputs turn-by-turn navigation instructions (via text and voice). Users can choose between the fastest and happiest routing in our app. Figure 5 shows the navigation screen of our customized PocketMaps application in the wild. The entire user data, including emotional prediction scores, is stored locally on the smartphone device. This privacy-preserving design allows HappyRouting to continuously monitor contextual driver data without compromising user privacy. Users retain full control, as they can switch to conventional fastest-route navigation at any time without data consequences.

5 Driving Study

The goal of our driving study is to gain an understanding of HappyRouting's user experience and its influence on a driver's emotions. The following study represents a preliminary technical validation designed to establish initial evidence for the feasibility of emotion-optimized routing. We envision that our study will lead to future investigations demonstrating that HappyRouting is effective on a large scale. We conducted a within-subject driving study to investigate differences in valence and arousal when using the fastest route compared to HappyRouting.

5.1 Participants

Participants were recruited through a dedicated mailing list of colleagues willing to conduct research studies. Participants did not receive compensation for their involvement in the study. Participants gave their explicit consent to participate in the study and formally agreed by signing an informed consent form, which explained the details of the study and their rights. Participants were informed about the goals and procedure of the study. Participants could retract the study at any time. An independent review board granted ethical approval for the study, ensuring compliance with established ethical standards and protocols. We recruited 13 participants (11 self-identified as male, two self-identified as female) with an average age of 27 ± (8.51) years. Six participants drive occasionally (i.e., less than 10,000 km/year), six participants drive moderate distances (i.e., between 10,000 and 20,000 km/year), and one participant is a frequent driver (>20,000 km/year).

5.2 Methodology & Procedure

The participants accessed a vehicle with a standard Android smartphone attached to the windscreen (see Figure 5). We gave the participants time to get familiar with the car and explained that they could drive like they normally do (e.g., listening to music). We asked the participant to use our HappyRouting application just like a common mobile navigation app. We selected start and end points that are approximately 15 minutes apart in terms of driving time, encompassing both rural and urban regions. This decision was influenced by the mean duration of journeys across the globe is approximately 15 minutes, although this value may fluctuate greatly depending on the country and other aspects [60]. Considering that commuting accounts for most trips [30, 67], we opted for an urban office location and a rural area as the two points in our real-world driving study.

The calculated routes were kept consistent for all participants to ensure comparability. The routing choice (fastest or happy routing) was hidden in the mobile application to avoid confirmation bias (i.e., blind route choice). The routing choice was randomized so that seven participants drove the happy route first, while six drivers were assigned to the fastest route first. While the start and end points were the controlled variables in the trips, it is important to note that factors such as the time of day, the specific vehicle used, and resulting traffic conditions were not regulated within the study parameters. These deliberate choices were made to maintain the study's closeness to real-world driving scenarios, intentionally varying only the two route options while allowing other factors like time of day, the specific vehicle used, and traffic conditions to simulate natural, uncontrolled driving conditions.

Overall, the one-way driving lasted approximately twelve minutes for the fastest route and 14 minutes for the happy route, depending on individual traffic conditions. Unlike the routes shown in Figure 1, the routes had very little overlap, with varying proportions of highways and secondary and tertiary roads. The study protocol is presented in Figure 6. For each assessment of the driver's emotional state (valence, arousal), we applied the self-assessment manikin (SAM) framework [12] with a five-point Likert scale. More detailed questions, such as the participant's driving experience, trip-time estimate, or route favorability, were asked after the drive and can be found in Table 4.

5.3 Results

Valence-Arousal-Dominance Analysis. We present the before and after analysis of valence, arousal, and dominance scores assessed with the self-assessment manikin questionnaire in Figure 7. We found that people gave higher valence ratings, i.e., positive attitudes, after taking the happy route. The mean valence score for happy routing before driving was 4.15 and increased to 4.62 after driving (11% valence score increase). We statistically compared the driver emotions before and after driving to assess the impact of HappyRouting on driver emotions compared to fastest routing. We used a Shapiro-Wilk test for investigating deviations for normality. Applying a Shapiro-Wilk test revealed a non-normal distribution for our measurements, $p < .001$.

We used Wilcoxon signed-rank tests for statistically comparing the emotion assessments within the routes. We calculate the effect size r as suggested by Rosenthal et al. [69]. A Wilcoxon signed rank test found a significant difference in valence before and after navigating through a happy route, $Z = -2.45$, $p = .007$, $r = 0.48$. In addition, we did not find significant before-after differences in valence, $Z = -0.83$, $p = .405$, $r = .23$, or arousal, $Z = -0.97$, $p = .334$, $r = .27$, when driving the fastest route. Overall, we found a positive trend in arousal when driving the happy route, though all expressed arousal levels have high variance. The high variance likely results from the fact that the driving task was perceived as relaxing or exciting on an individual driver's basis. Again, a Shapiro-Wilk test showed a non-normal distribution for arousal, $p = .025$. There was no significant difference in arousal before and after driving the happy route according to a Wilcoxon signed rank test, $Z = -1.65$,

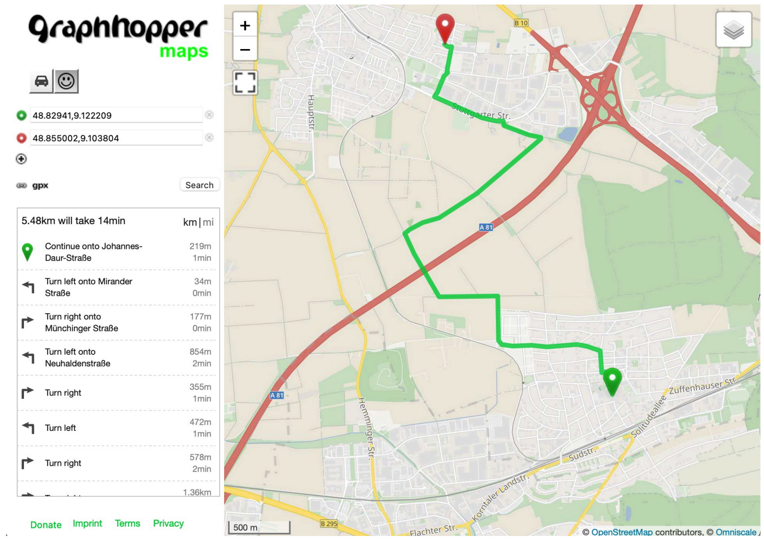

Figure 4: GraphHopper web-server for Happy Route Optimization in a 2D-layout.

Figure 5: Implemented navigation app that supports normal and happy routing. The app is placed on the windshield and has the same functionality as normal navigation apps (turn-by-turn navigation, voice output for hinting next directions).

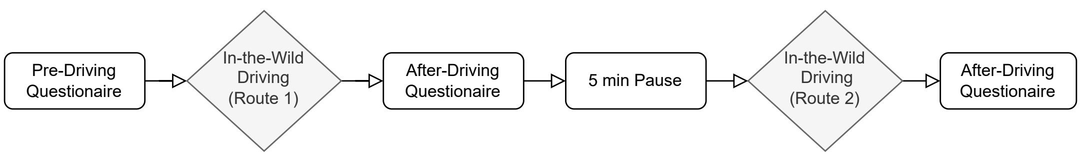

Figure 6: Experimental design of the emotional navigation driving study. The endpoint of the second drive was set to be the start point of the first drive.

$p = .1$, $r = .46$. This finding contrasts many empathic car applications that seek to optimize arousal levels for safety reasons [13, 14]. We did not find significant before-after differences for the dominance scores when driving the fastest, $Z = -0.63$, $p = .527$, $r = .17$, and happy route, $Z = -1.41$, $p = .157$, $r = .39$. To ensure the findings were not biased by the gender imbalance in our sample (11 men, 2 women), we performed a robustness check by analyzing the male-only subgroup ($N = 11$). For the happy route, the results remained consistent: valence scores increased significantly from before to after driving ($p = .025$) while arousal ($p = .057$) and dominance ($p = .157$) showed no significant change. These subgroup results confirm that the observed emotional improvements are present even when controlling for gender.

We statistically compare the perceived emotions for the fastest and happiest route after the driving trials. However, a Wilcoxon signed-rank test did not reveal a significant difference for valence, $Z = -1.89$, $p = .057$, $r = .52$, arousal, $Z = -1.81$, $p = .07$, $r = .5$, and dominance, $Z = -1.00$, $p = .317$, $r = .27$. Route order had no statistical impact on participant ratings. In total, 54% began with the happy route, showing a balanced setup.

Happy Navigation Driving Behavior. Our driving questionnaire showed high variability when and how drivers wanted to use happy navigation functionality. After the driving experiment, we asked the participants how much time they would sacrifice for a happy route, assuming 20 minutes for the fastest route. 9 of 13 participants answered with 3 to 5 minutes, while 3 of 13 drivers would only spend 1 to 3 minutes additional drive time. One participant stated the willingness to even spend more than 10 minutes of additional time to drive the happy route. These results are consistent with the web survey by Pfleging et al. [63], which states that participants would take on average 20.9% more time for an experience-optimized route compared to the fastest route. While the fastest route took on average 2 minutes less time, 8 of 13 participants perceived the happy route as shorter. Combined with the finding that subjects had a more positive emotional state after driving the happiness route, we conclude that a happiness route may positively influence the perceived travel time. Furthermore, in our study, 11 out of 13 participants stated that they would use the app in their leisure time when they did not have time pressure. Interestingly, many participants responded to use our navigation only on the weekend (P9, P10, P12), preferably in the summer (P1, P2, P3, P4, P9, P10, P12), and not at night when the driving scenery is not visible (P8, P13). P2 mentioned a preference for using happy routes in the event of a traffic jam, which would enable the choice of less crowded, more relaxed, and undiscovered routes.

System Acceptance. In response to the question "How likely would you be to use this system?" on a scale of 1 (not at all likely) to 5 (very likely), 11 of 13 participants gave scores of 4 and 5. The

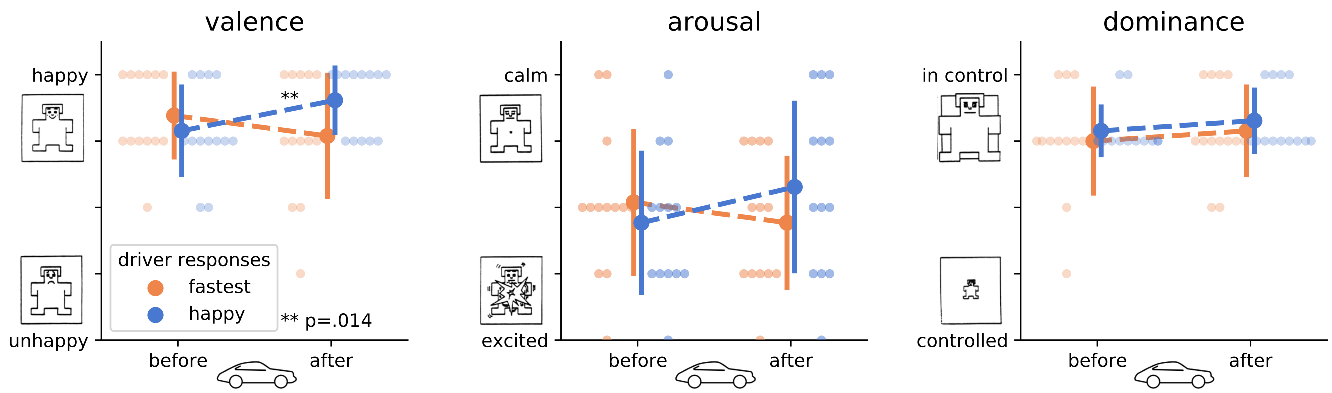

Figure 7: Before and after driving analysis of valence (left), arousal (middle), and dominance (right) questionnaire answers of the driving study. The lines indicate the responses' standard deviation (vertical) where the means are connected via the dashed line. The asterisk indicates significance. Fast and happy routes were assigned blindly and by random succession.

study participants introduced ideas for pairing happy navigation with other in-car technology. The most prominent response was that many people associate happiness with music while driving. Therefore, many suggestions were made to automatically select the music to match the route, or vice versa, to select the route to match the music better.

We also asked the participants in a free-response question: "Do you think there are any societal and ethical implications of this navigation functionality? And if yes, which one?". Many participants said that they did not see any ethical or societal implications (P6, P7, P9, P11, P13). Participants also responded with higher energy consumption costs and a more environmentally harmful behavior when driving a happy route (P1, P3, P10). P10 stated that there was a problem with happy routing only recommending pleasant routes so that other less happy predicted locations are not seen, creating a self-reinforcing effect of what people see.

6 Simulation Study

To offer a broad assessment of the recommended happy routes by our system, we performed an offline numerical simulation analysis.

6.1 Experiment Design

First, we downloaded and computed the emotion prediction layer for a map of a medium-sized city (12 × 12 km). We sampled a large number of equally-distributed, random start and end points ($N = 1000$) and searched for the happy and fastest routes. We then analyzed the route trajectories segments by computing several characteristics such as road types, greenness, traffic conditions, and curviness. Furthermore, we computed the travel time, distance, and the overlap of the fastest and happy routes.

6.2 Route Time Analysis

We anticipated that taking the happy route would increase the travel time. Figure 8 shows the relationship of the navigation mode on travel times using $\lambda = 20$. Using linear regression, we found that a one-minute increase in fastest routing requires in average 1.26 minutes (75.6 sec.) more time to drive using happy routing. Only 9% of the start-end coordinates resulted in a situation where the happy route is identical to the fastest route ($overlap = 100\%$). The time difference can be substantial in individual cases. Therefore, we stress a transparent time forecast when recommending happy routes to drivers. We conclude that the factor λ should rather be regarded as an internal technical parameter (see the influence of λ in Figure 9) instead of a user-adjustable parameter. Higher λ results in increased average travel time and, therefore, causes longer travel times. Hence, λ can be adjusted dynamically to suit the societal driving context.

6.3 Road Characteristics

We analyzed the recommended happy and fastest route for their road types with results shown in Figure 10 and Figure 11. As the drive-time was normalized per individual route, the values of the bars do not add up to 100%. We tested whether the distribution of the different road characteristics is significantly different ($p < .01$) using a non-parametric Mann-Whitney U test. Compared to the fastest route, we found that happy routes consist of more road segments with a higher predicted happiness score, higher curviness, higher freeflow speed, and maximum speed.

Curvy roads tend to increase driving enjoyment but also inhibit driving accident risks [39]. Unhindered traffic scenarios can be captured by our proxy variable free-flow speed, which is higher for happy routes and increases driver well-being [68]. We detected no significant effect of the satellite-image-derived greenness (known part of the HSV spectrum) in happy routes compared to the fastest route ($p = .29$). Finally, we found that on-average happy routing includes significantly more residential roads. We believe that this is due to the fact that residential roads often have reduced traffic and may reduce drivers' stress, leading to a more happy emotional state. In contrast, the recommended fastest routes contained significantly more living street and primary road segments, which often require more driver attention. As stated before, these findings are based on a large sample size and do not represent an individual recommended route.

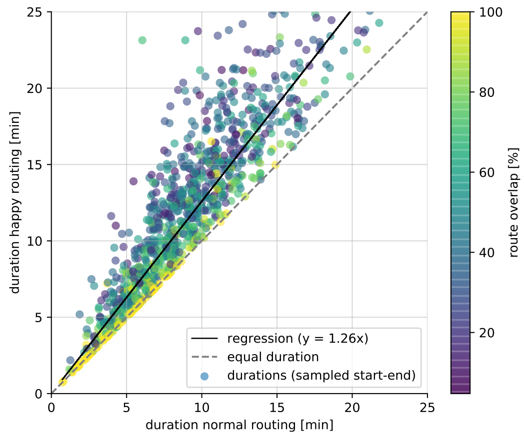

Figure 8: Scatter plot of drive duration of normal vs. happy routing. The points are mostly on the top-left of the equal-travel-time line, meaning happy routing generally takes longer to drive. We set λ to 20. The fitted regression ($R^2 = 0.81$, $BIC = 1969$) with a slope of $\beta_1 = 1.26$ ($p = .00$) means that a 1-minute increase in normal routing will take 1.26 minutes (75.6 $sec.$) more time to drive using happy routing.

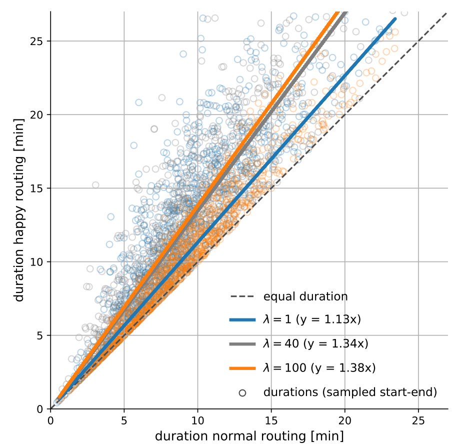

Figure 9: Influence of emotional weighing factor λ on happy routes. The additional travel time for happy routing does not scale linearly with the emotional weighing factor λ. On average, the setting $\lambda = 40$ achieves a similar time divergence to $\lambda = 100$.

6.4 Computational Characteristics

Navigation systems deployed in the wild require high scalability. To assess the computational complexity of our system, we computed the execution time of the routing endpoint (GraphHopper). On the 12×12 km map, our system needs to perform emotion prediction on 21,673 unique edges, caching the corresponding data in the optimization graph. The cache is needed because the input data is collected from various APIs, which makes on-demand prediction attainable when optimizing the route. In a subsequent step, the execution time for recommending happy routes is 0.08 ± 0.075 seconds and takes longer to compute than the fastest routing 0.01 ± 0.004. With recommendation times smaller than 1 second, our system is highly time-efficient and user-friendly.

7 Discussion

With HappyRouting, drivers perceived a higher valence when using the happy route than the fastest route, showing that choosing emotionally positive routes contributes to a driver's well-being. In the following, we discuss the implications of our results.

7.1 Tradeoff Between Valence and Route Duration

In contrast to previous work [80], we empirically evaluated the impact of HappyRouting in real-world driving scenarios. Our results suggest a tradeoff between the duration of the fastest route and the perceived valence of driving the happy route. Although the happy route takes longer, our participants subjectively preferred HappyRouting for their navigation to improve their emotional well-being. This confirms previous findings regarding the implementation [53, 80] and user-centered evaluation in laboratory settings [10, 43]. In this context, our results are in line with previous research that participants prefer emotional navigation [43] . However, due to the longer travel times, most of our participants indicated that they would prefer the HappyRouting if they were not pressed for time. Overall, numerous transportation studies have researched the willingness to pay, i.e., how much time and money people are willing to spend for an alternative route choice. The admissible detour duration is highly dependent on the situation and the individual [18]. Self-centered situations, such as avoiding danger, reach much higher detour acceptance and decline more slowly with longer detours. The user acceptance drops to the 25% plateau at 8-min detours for jam-related situations [52].

In addition, our study results suggest other modalities for controlling driver emotions by combining the in-vehicle environment with the suggested happy route. For example, participants suggested to explore music in combination with happy routes to enhance feelings of happiness. Using individual preferences for the in-vehicle environment as an additional variable can lead to emotion prediction models that ultimately reduce driving time. Additionally, complementary interventions such as adaptive ambient lighting, personalized music selection, seat massage, and biophilic interior elements could work in combination with HappyRouting.

7.2 Benefits of HappyRouting

The emotional state of drivers plays a critical role in road safety, as it has been shown that negative emotions, such as anger, can significantly increase accidents [78]. More specifically, it has been demonstrated by identifying common emotional triggers based on their originating source through self-report driving that the most frequently elicited negative emotions stem from the car's navigation

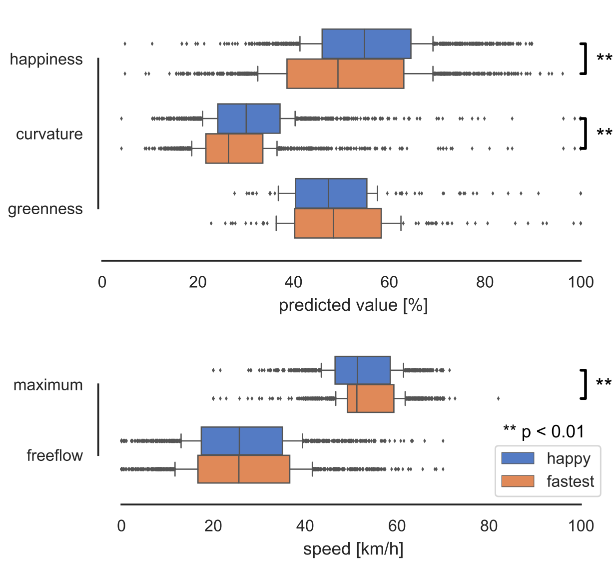

Figure 10: Characteristics of happy route vs. fastest route. Distribution of happiness, curviness, greenness, max_speed, and freeflow_speed for the two routing modes.

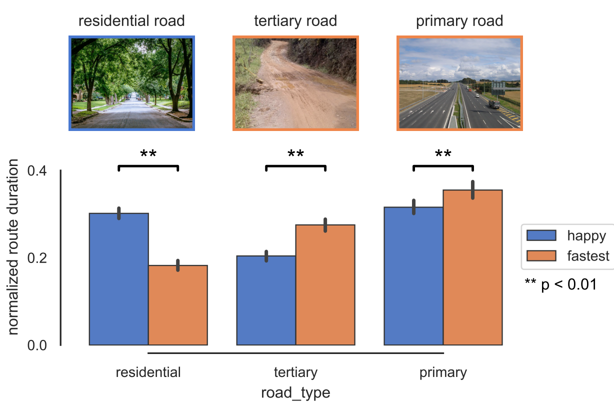

Figure 11: Analysis of road types of happy routing vs. fastest routing. We assessed the road type of every road segment (x-axis) and computed the drive-time normalized route duration (y-axis). All presented road types have been tested to be significantly different ($p < .01$). Residential roads were found in living areas, primary road types are major highways linking large towns, and tertiary roads connect minor streets to more major roads.

interface. Therefore, car systems that propose appropriate interventions, such as improving routing choices, are helpful in enhancing road safety and improving the driving experience. Future work will examine the safety reduction potentials of different route choices. By promoting positive emotions through navigation choices, HappyRouting introduces a novel paradigm in safety-aware routing, reducing emotional distress and fostering a more composed driving experience.

While our study focused on emotional valence as the primary outcome, driver safety represents an equally important consideration. Our study validated emotional impact as a first step. Future work should integrate physiological safety indicators such as fatigue detection, drowsiness monitoring, and stress biomarkers. Such metrics would enable a comprehensive assessment of whether emotion-optimized routes also reduce accident risk factors. Preliminary evidence suggests that positive emotional states correlate with safer driving behaviors [62], but direct measurement in the context of affective routing remains unexplored.

7.3 Using HappyRouting for Other Transport Modalities and Types

HappyRouting generates routing decisions that can be used in various other transportation modalities once the foundation for a context-aware machine learning classifier is established. With a few modifications, HappyRouting can apply emotion-based navigation , for example, for cyclists, by predicting emotionally pleasant cycling routes. We propose incorporating advanced contextual sensors when optimizing happy routes for other road users (e.g., pedestrians or cyclists) by extending the feature set to include elevation information and information about road intersections. For the application of HappyRouting in pedestrian routing, we recommend extending our feature set to include traffic-banning features, as these have been shown to influence valence [61] positively. Such a set of features can extend existing work investigating the relevance of contextual driving features regarding classification accuracy.

Implementing HappyRouting for autonomous vehicles (SAE Level 2 and beyond) presents several unique challenges and opportunities. When passengers are freed from the driving task, factors such as smooth acceleration, scenic views, and journey duration may become more salient than road characteristics that matter for manual driving. The entire feature set may require reconceptualization. Considering the emerging problem of motion sickness in automated vehicles [21], a traffic jam may be more acceptable in favor of less crowded roads in the countryside. As users engage in various primary activities, such as working or watching movies, future research should explore the emotional impact of these activities on driving.

7.4 Ethics & Societal Impact

We emphasize an ethical and transparent use of HappyRouting for application purposes and stress that emotions are intimate, personal, and vulnerable [2]. The Emotional Artificial Intelligence ethics guidelines by McStay et al. [56] provided us with a meaningful reference to cover personal, relationship, and societal aspects.

Our approach is privacy-aware because it uses a machine learning model based on an aggregate, anonymized dataset provided in advance by a set of volunteers rather than subconsciously assessing the emotions of individual HappyRouting users. On the other hand, we also observe clear limitations in our dataset regarding cultural and regional diversity, as well as the explainability of the resulting algorithm choices. Future empathic car interfaces must communicate how and what data is assessed to clarify how this subsequently affects the users' privacy.

Undeniably, the regulation of emotions by technological systems is highly controversial, as psychological effects are largely unknown. Avoidance of negative situations, for example, is an essential strategy of human emotion (self-)regulation [55], but also an implicit result of our system's promotion of positive emotions. Studies with individuals have shown that situation avoidance results in decreased learning and adaptation abilities, as well as social and anxiety disorders [1]. Therefore, we emphasize that such short- and long-term effects must be investigated in future work.

Our study of route characteristics shows that heavily traveled routes are often avoided in favor of quieter routes. To us, this is a clear indication for future work, as these externalities at a large scale can potentially affect residential areas, parks, or nature, as Johnson et al. note [46]. This raises concerns that optimizing on happiness could further contribute to the frustrations about increased traffic in previously low-trafficked neighborhoods.

We showed that routes proposed by HappyRouting result in increased travel times, ultimately bound to higher energy consumption. We acknowledge this tension between individual well-being and collective environmental responsibility. Future versions of HappyRouting could incorporate carbon-awareness as an additional optimization constraint, presenting users with the environmental cost of emotional optimization. Such transparency would enable drivers to make informed tradeoffs aligned with their values. From an environmental standpoint, this higher energy consumption might be harmful. Overall, no ethical guideline would prioritize one's happiness over the negative externalities that may result from their navigation choice [6]. Moreover, prioritizing personal happiness over social and environmental responsibility may also perpetuate a culture of individualism that values personal satisfaction over the greater good. Therefore, it is imperative to consider the broader social and environmental implications of routing decisions, while striving to balance personal happiness and the well-being of others and the planet. Certain route choices might affect the safety of traffic participants, for example, due to a model's preference for specific road types. These and many other route characteristics must be communicated transparently to the users to promote their autonomy and enable highly informed choices [56]. Alternative strategies could comprise correction terms applied to our optimization, for example, when the routing choice is not desirable on a societal basis (e.g., routing through densely populated areas) [46].

7.5 Limitations & Future Work

Our work takes the first steps towards a novel type of empathic car interface based on emotional predictions and optimizations through routing. To achieve this goal, we accepted several limitations in the domains of psychology, algorithms, and user experience. First and foremost, the psychological model of fostering well-being through aggregation of positive emotions is deliberately oversimplified, as discussed in Section 3. Future models could operate on a diverse emotional flow [50], which requires significant changes to the optimization method and its proven graph algorithms. Yet, the system's ability to generalize across unseen environments relies on its subject-independent emotion prediction approach. While individual adjustments could further refine classification accuracy, our current implementation provides a scalable solution for real-world deployment.

Utilizing emotion-related signals during driving would enable the dynamic updating of the predicted emotional weights and real-time adaptation of the happy route. This feature can be easily integrated into the current system architecture, but it should be approached with caution as it has the potential to be perceived as privacy-intrusive. However, the benefit of our non-interactive emotion navigation system is that it allows for an empathic interface without compromising privacy during operation, and the option to switch to a different routing modality can be easily selected at any point during the journey.

HappyRouting requires the ability to simulate the driver's emotions for any road segment at any time while considering contextual information like traffic, road types, and speed limits. A key design decision for simulation lies in the choice between subjective and objective metrics for characterizing user emotions. HappyRouting relies on a dataset containing self-expressed and thus subjectively perceived emotions for prediction. Consequently, we base the simulated emotions on discrete representations of emotions, as identified by Ekman [27]. The use of subjectively expressed emotion labels could also be accompanied by the integration of physiologically derived labels into the emotion prediction model [45]. By incorporating data such as heart rate variability, skin conductance, muscle stiffness [3], and facial expressions [53], a hybrid model (objective & subjective) could further enhance the accuracy of the emotion predictions. Related works by Wang et al. [80] and Zepf et al. [85] highlight the potential of bridging live emotions with future recommendations or an adapted system behavior. At the same time, the car offers only a limited set of remotely accessible contextual features for predicting driver emotions, making the modeling complex.

Our navigation framework is based on an emotion prediction layer that can be easily adapted to additional modalities. Weighting objective parameters, such as the greenness score [4], could promote user-specific preferences without requiring a personalized emotion model. On the other hand, user-dependent models can further increase the accuracy, as shown in related work [3, 10].

We acknowledge the sample size limitation (N=13), which impacts statistical power. A follow-up longitudinal study with a larger and more diverse participant pool would strengthen our findings and enable the examination of long-term behavioral effects of affective navigation. Notably, our research represents the first attempt to conduct such a study in a real-world driving environment, including a user evaluation with a functional routing application for unseen roads. We plan to conduct a large-scale study with a more extensive participant pool to address this limitation, incorporating varied routes and study durations. This will be achieved by leveraging crowd-sourcing methods, for example, by distributing HappyRouting through app stores, thus extending the reach of HappyRouting to a broader user base and including diversity in our dataset.

Finally, we recognize limitations in explaining the overall recommendation process to the end user, which is ultimately crucial for the ethics and transparency of our system. The transparency can lead to placebo effects, where the description of using an allegedly adaptive AI-driven system biases the perceived utility of the system for drivers [51]. In future work, we plan to summarize how route recommendations were computed on an individual user's basis and research how to communicate key emotional route segments [13]. Finally, further long-term experiments with a larger variety of roads and routes under vastly different conditions are needed to produce the necessary evidence of the proposed model's ability to find happy routes. These long-term studies in the wild may help better to understand the effects and societal impact of affective routing.

8 Conclusion

This paper presents HappyRouting, a new type of empathic interface capable of navigating by positive emotions. We used personal, environmental, and road-specific information to define a custom emotion routing graph that optimizes routes for happy emotions. This paper validates the novel routing concept through several validations, demonstrating both external and internal validity. The machine learning classifier used to predict emotion weights has been shown to accurately predict emotions on unseen road elements and driver emotions. Furthermore, a real-world driving study and simulation study demonstrated its generalizability to extend to unknown routes. Our pilot user study showed that HappyRouting elicits positive emotions through navigation. HappyRouting requires more driving time, which our participants accepted as long as the circumstances allowed it (e.g., no time pressure). This evaluation was a preliminary check of the underlying technical concept, rather than a definitive, large-scale user study of its effects. Our work is not only relevant to driving but can also be applied to other areas of mobility and autonomous driving. We are confident that the presented process of simulating emotions and evaluating different paths through many user journeys can be generalized to a wider variety of use cases. To encourage the reproducibility of this paper and engage research in this area, we published the source code of our system and the data set for further analysis by the research community[10]. We encourage the research community to build upon this foundation with larger-scale studies, diverse populations, and longitudinal designs that can capture the sustained effects of affective routing on driver well-being and safety.

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A Appendix

Classifier Feature Importances

We analyzed how decisive each contextual input feature is for our human emotional state classification model. We extracted the feature importance (Gini impurity) of the input variables in a leave-one-participant-out situation in Figure 12. The variable 'greenness' shows the highest importance for the classifier in predicting the likely emotional state on the road. This likely comes from the fact that roads with high green value scores likely go through rural areas with less traffic flow influencing emotions positively. Thus, 'greenness' is a good proxy input for positive emotional states [11].

The feature importances are aggregate metrics and do not convey participant-dependent importance measures for a specific routing choice (local feature importance measures such as SHAP values are needed). Here, we only analyzed the feature importance of the emotion classification model, a route-specific analysis of the road properties can be found in Section 6.3.

In-the-Wild Driving Study

The in-the-wild driving evaluation routes were 7.5km (fastest) and 8km long and went through urban and rural neighborhoods. In Table 4 we present the study questions used in the in-the-wild driving evaluation of our system.

Emotion Classifier Dataset

Dataset Generation Procedure. An iOS app was developed to track GPS and video during car rides. The smartphone app gathered information about the road type, greenness, traffic flow, and other variables to describe the driving context. Upon hearing a beep, participants were asked to self-report their emotions every 60 seconds. The participant's self-reported emotions were the ground truth in this real-world experiment. The timing of these prompts was fine-tuned in a small pre-study to ensure safety and minimize distraction. Most participants found these prompts non-disruptive, responding within an average of 1.8 seconds. Additionally, participants were provided with a list of basic emotions before the experiment. Participants were drawn from a group of willing colleagues contacted via a mailing list, prepared by downloading our iOS app and securing a windshield smartphone holder. Before their next drive, they engaged in a remote conversation with the study instructor, sharing demographics, driving habits, and pre-ride emotions. Following an introduction to the app, they commenced recording, drove to their destination, saved recordings post-ride, and subsequently connected with the instructor. During this call, they discussed noteworthy driving incidents and their emotional experiences before,

[11]The training data of the classifier is unbiased, containing green areas and urban road data.

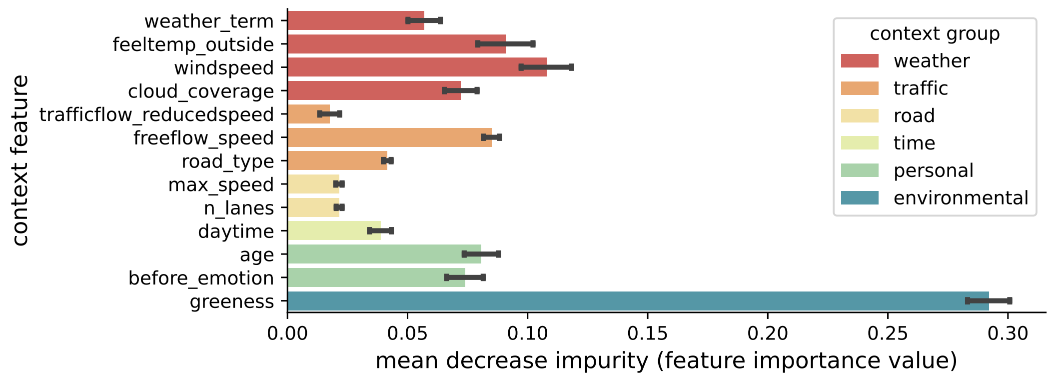

Figure 12: Feature importances measured by the mean decrease of Gini-impurity for the Leave-One-Participant-Out cross-validation.

Table 4: Questionnaire of the in-the-wild driving experiment.

Question	Example answer
What car do you drive?	VW Golf
Your age	39
Your sex	female
How frequent do you drive? (km/year)	occassional: <10.000km/year
When did you drive today?	in the morning
How do you feel before driving? (valence)	3 (of 5)
How do you feel before driving? (arousal)	5 (of 5)
How do you feel before driving? (dominance)	4 (of 5)
Other notes / suggestions?	None
What navigation mode did you drive?	navigation mode 2
How do you feel after driving? (valence)	2 (of 5)
How do you feel after driving? (arousal)	4 (of 5)
How do you feel after driving? (dominance)	4 (of 5)
Were there any specific incidence while driving?	Slow trucks in front of me
Do you know the route 1? (Have you ever driven this route?)	Partially
How would you describe route 1?	Slow, green and full of Blitzer
Select all adjectives that in your opinion describe route 1 (select as much adjectives as you want)	Green, Smooth, Relaxing
How do you feel before driving? (valence)	2 (of 5)
How do you feel before driving? (arousal)	4 (of 5)
How do you feel before driving? (dominance)	4 (of 5)
What navigation mode did you drive?	navigation mode 1
How do you feel after driving? (valence)	3 (of 5)
How do you feel after driving? (arousal)	3 (of 5)
How do you feel after driving? (dominance)	3 (of 5)
Were there any specific incidence while driving?	Lkw and trucks in front of me
Do you know route 2? (Have you ever driven this route?)	Yes
How would you describe route 2?	A lot of construction work and interruptions
Select all adjectives that in your opinion describe route 2	boring, bumpy, relaxing
I agree with the following statement: "I feel route 1 is faster than route 2"	equal
I agree with the following statement: "I feel route 2 is faster than route 1"	equal
Which route would you rather choose?	Route 1
Why?	Felt smoother
I agree with the following statement: I feel route 1 makes me happier than route 2? (ordered and preprocessed response)	yes
Do you feel route 2 happier than route 1?	no
Do you feel route 1 happier than route 2?	yes
How much time you would like to sacrifice to drive a happier route (assuming 20 minutes drive for fastest route)?	3-5 minutes
What did you do apart from driving? Applies to both driving modes	hearing music/radio, talking to passengers
Does something about the Happy Navigation idea bother you?	You drive more
When (under which circumstances) would you use Happy Navigation?	When I am somewhere new (e.g., holiday), start the day smoother, when I have more time, when I want to listen to a podcast
What determines your ideal happy driving route (road elements, scenery)?	Green, drive by forest, less cars, rapsfelder
When would you use Happy Navigation?	In the morning
What features in the car would you find interesting using the Happy Navigation?	I would want to see if I drive the happy route (transparency)
How likely would you use this system?	3 (of 5)
Do you think there are any societal and ethical implications of this navigation functionality? And if yes, which one?	Fuel or energy consumption increases, invisibility of unhappy places and roads and their existences, self enforcing effect
Other notes/suggestions?	None

during, and after driving. Ethical approval was granted by the institutional review board of the university department.

Emotion Labeling. For the emotion classifier, we leverage existing approaches that link real-world context and emotions [9, 10]. The authors built an iOS app to record GPS and video during car rides and compute variables continuously. Participants were asked to use this app and attach their phones to the windscreen during their next car ride. The authors recorded the daytime and participants' emotions at the ride's beginning. A beep tone was triggered every 6 seconds for participants to verbally provide their currently perceived emotions. This emotion probing corresponds to the *in-situ* categorical emotion response (CER) rating for collecting data on emotional experiences in vehicles [23]. Before starting the experiment, participants were instructed about the set of available emotions (i.e., Ekman's basic emotions [26]). The verbally expressed emotions were recorded and analyzed afterward using a speech-to-text algorithm. In a pre-study (N = 5), the time interval of the prompts was optimized to ensure safety, minimize annoyance, and appropriately cover the felt emotions. Participants found these prompts non-disruptive, responding within an average of 1.8 seconds.

Dataset Description. The dataset contains 26 participants (17 male and 9 female) with an average age of 30 years (SD = 5.56) from Germany, Brazil, and Poland. Most driving sessions (69%) occurred in Germany, followed by Brazil (23%) and Poland (9%). Participants reported driving frequently (57% over 30,000 km/year), moderately (19% between 10,000 and 20,000 km/year), or less frequently (23% below 10,000 km/year). Driving sessions included rural and urban roads, lasting an average of 24 minutes (SD = 12, min = 7, max = 52) with 5.6 changes in road type per ride. Participants typically expressed 5.21 distinct emotions during their rides, with an average time of 2 minutes (SD = 2.5 minutes) between each expressed emotion.