The Virtual Driving Instructor: Multi-Agent System Collaborating via Knowledge Graph for Scalable Driver Education

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Abstract

This paper introduces the design, development, and deployment of a Virtual Driving Instructor (VDI) for enhanced driver education. The VDI provides personalized, real-time feedback to students in a driving simulator, addressing some of the limitations of traditional driver instruction. Employing a hybrid AI system, the VDI combines rule-based agents, learning-based agents, knowledge graphs, and Bayesian networks to assess and monitor student performance in a comprehensive manner. Implemented in multiple simulators at a driving school in Norway, the system aims to leverage AI and driving simulation to improve both the learning experience and the efficiency of instruction. Initial feedback from students has been largely positive, highlighting the effectiveness of this integration while also pointing to areas for further improvement. This work marks a significant stride in infusing technology into driver education, offering a scalable and efficient approach to instruction.

Introduction

In an increasingly digital world, traditional educational models, including driver education, are rapidly evolving (Gabriel et al. 2022). Simulators have long been a part of driver training, and with the recent advances in artificial intelligence (AI), there is a significant potential to enhance and expand this approach. This paper discusses the design, implementation, and deployment of a Virtual Driving Instructor (VDI) that employs a multi-agent system, knowledge graphs, and Bayesian networks to assess student performance in a driving simulator, providing immediate, personalized feedback. To the best of our knowledge, there are no other AI-based driving instructors that provide such comprehensive feedback.

In conventional driving training, the full attention of an instructor is required for each student, limiting the scalability of the instruction process. However, with our VDI, we aim to transform the landscape of driver education by enhancing scalability and standardization while reducing cost.

Through handling routine instructions and offering immediate feedback, the VDI facilitates an environment where human instructors can monitor multiple students in parallel. This not only increases the efficiency of the education process but also significantly optimizes the role of human instructors, enhancing their capacity to manage and supervise more students concurrently. From our trials, we found that a 1:3 teacher-student ratio was feasible, while a 1:5 ratio could overwhelm the instructors. This suggests that further refinements to the user interface and pedagogical practices may enable more efficient multi-student instruction.

The use of VDI also introduces standardization to driver education, ensuring all students learn from a consistent curriculum regardless of their location. Traditional in-person training is often influenced by local traffic conditions, leading to variability in the learning experience. Our system mitigates this problem by offering standardized simulated traffic scenarios.

Moreover, employing a VDI could drastically cut down the cost of driver education. Currently, the human instructor's fee accounts for a significant part of a driving lesson's cost. By partially substituting human instruction with AI-based instruction, we estimate the cost could be reduced significantly, which could be particularly beneficial in countries like Norway where driver education maintains a high standard but also comes with a substantial cost.

Lastly, the VDI provides a safe platform for training drivers for scenarios that are difficult to replicate in real-world training, such as certain accident situations. This can significantly enhance the student's preparedness for unexpected real-world situations.

In this paper, we delve into the architecture of the VDI, encompassing its design, implementation, and deployment within the context of a driving school environment. By combining AI and driving simulation, we aim to enhance the learning experience for students, improve the efficiency of instructors, and ultimately, foster safer, more competent drivers.

Related Work

Various approaches have been adopted in the development of virtual driving training and analysis systems. A VDI that employs a flexible multi-agent architecture, akin to our work, serves as an exemplary approach in the domain of intelligent driving education systems (Weevers et al. 2003). The system adeptly evaluates real-time student driving behaviors, making necessary adjustments to the simulated environment. The VDI, designed with modifiable architecture, accommmodates numerous 'awareness' types, each represented by distinct agents. This enables adaptive, context-aware feedback. Their work underscores the efficacy of multi-agent systems in driving education and the potential for high-context feedback.

Analytical tools, such as DriveLab (Heffelaar et al. 2014), which incorporates a behavioral analysis tool, a 3D eye tracker, and a mid-fidelity simulator, offer comprehensive parameters, from distraction detection to cognitive workload assessment. Nevertheless, it is designed for analysis rather than instruction.

The translation of research projects into practical, simulator-based training systems has been documented before. An example of this is a truck simulator's deployment, which underlines the value of a concurrent engineering approach that involves researchers, simulation experts, and end-users (Romoser and Hirsch 2012). This process, which evolved over a span of more than four years, comprised six iterative implementation cycles, each cycle building upon the last based on continuous feedback. This case study illuminates the critical roles and interactions among diverse stakeholders throughout the design, testing, production, and delivery stages.

Systems like CarCOACH (Arroyo, Sullivan, and Selker 2006) strive to enhance driving habits through real-time feedback derived from vehicle sensor data. The study found that the strategic scheduling of feedback, particularly negative feedback, can mitigate detrimental effects on performance and alleviate frustration.

Another study (Hirsch and Bellavance 2017) highlights the impact of driving simulator–based training (DSBT) on real-world driving. They found that learners who underwent DSBT recorded fewer infractions, and maintained similar crash rates compared to those without DSBT exposure. This indicates that DSBT can effectively improve road safety without fostering overconfidence, adding weight to the potential value of simulated training in driver education programs.

Meanwhile, BeAware (Baumgartner et al. 2014), a software framework designed for managing complex environments such as road traffic, integrates perception, comprehension, and projection layers. These layers collaboratively gather, interpret, and anticipate situational data, reducing information overload and aiding operators in critical situations. Real-world traffic scenarios and data have demonstrated BeAware's effectiveness.

Driving Simulation and Virtual Instruction: A Unified System

The core of our system revolves around a hybrid AI system called the Virtual Driving Instructor (VDI) (Sandberg et al. 2020; Rehm, Reshodko, and Gundersen 2023). This application interfaces with high-fidelity driving simulators (Allen et al. 2007) to assess student performance and provide real-time, personalized feedback. The system's flexibility allows the simulators to be stationed at various locations while maintaining central control at a teacher station. This structure enhances the learning experience by allowing multiple students to receive personalized instruction simultaneously.

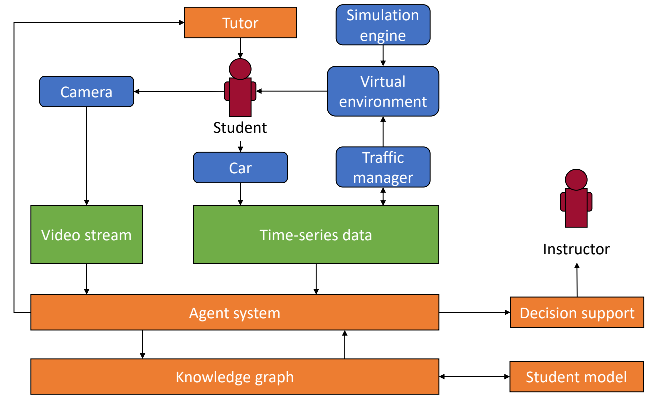

Figure 1: Overview of the system containing the driving student and the instructor in red, all the simulator components in blue, shared data in green, and the VDI components in orange

Figure 1 presents a holistic overview of the entire system. At its core is the student, who is seated in the car and navigating through a virtual reality environment. This environment is generated by the simulation engine, which leverages the Unity gaming engine (Unity Technologies 2022) and a traffic manager. The traffic manager orchestrates the movements of other virtual road participants, such as cars, trucks, and pedestrians (Lopez et al. 2018).

A camera positioned within the car captures the student's face, producing a real-time video stream. This video stream, along with live data from the car and the traffic manager, is transferred to the VDI via a shared memory system.

The multi-agent system within the VDI processes this data and logs the derived insights in a knowledge graph (Hogan et al. 2021). For example, the gaze estimation agent (Rehm et al. 2021) within the VDI uses the video stream to monitor the student's eye movements, determining in real-time which of the predefined gaze zones (Vora, Rangesh, and Trivedi 2018) the student is currently looking at. These gaze zones include areas such as the mirrors, blind spots, speedometer, and the view forward through the windshield.

This information from the knowledge graph aids the tutoring agent that provides immediate, personalized feedback to the student. Moreover, it offers decision support to the human instructor, enabling them to oversee multiple students simultaneously.

Upon the conclusion of a driving session, all data from the knowledge graph is fed into the student model (Romoser 2011). This model keeps track of the student's progression and assesses the competency level of various skills across all sessions.

Driving Simulator

The driving simulators, as shown in Figure 2, offer an immersive experience built around actual vehicles. This enhances the authenticity of the learning process with steering

Figure 2: High-fidelity traffic simulator developed at Way AS. A real car is mounted on the motion platform in the center. Surrounding the car is a projection screen wall with six different view channels projected at the driver's front.

wheels, pedals, and all the instruments of a real car. On the center console, a screen is mounted showing the in-car dashboard. This dashboard provides the student with information about the lesson and textual feedback during and after the lesson. This realistic environment contributes significantly to the overall realism of the driving simulations. The VDI is designed with generic interfaces, allowing integration with various driving simulators. At present, it is compatible with the immersive driving simulators depicted.

In preparation for every lesson, students are presented with a briefing video on the in-car dashboard. This informational guide explains the expectations and key aspects of the upcoming lesson, providing crucial pointers on appropriate behavior for the anticipated driving scenarios. This method not only prepares students effectively for their sessions but also reduces the workload on driving instructors.

Virtual Driving Instructor

The VDI is a hybrid AI system developed to instruct and provide feedback to a driving student operating in a traffic simulator. The VDI comprehensively assesses the student's performance across a range of driving situations. By constantly evaluating and responding to the student's actions, decisions, and adherence to road rules, it offers immediate, contextually relevant feedback. The VDI incorporates two key modules: the Real-time Assessment and Feedback Module (RTAFM) and the student model. The RTAFM operates during the driving session and includes the agent system, the knowledge graph, the tutor, and the decision support component (see Figure 1). Meanwhile, the student model activates post-session, focusing on evaluating the student's skill level, learning progression, and delivering a summarized feedback debrief.

Real-time Assessment and Feedback Module (RTAFM): Central to the RTAFM is the knowledge graph, which serves as a shared representation of the environment and the VDI's internal states. The knowledge graph is built on a property graph model (Hogan et al. 2021) that allows both nodes and relationships to be characterized by attributes. The graph is divided into static and dynamic nodes. The static part includes details like the layout of the road network and road signs. In contrast, dynamic nodes are responsible for real-time updates, tracking and reflecting changes as they occur within the simulation environment. They record various live time-series data, including but not limited to, the vehicle's position and speed, as well as information from the traffic manager. Further, dynamic nodes encapsulate the reasoning results of the agents operating within the RTAFM, providing a continuous appraisal of the student's driving performance.

Upon the conclusion of each driving session, the knowledge graph is stored in a database. This persistently stored data becomes instrumental for longitudinal assessments and insights.

Building on the foundation of the knowledge graph, the RTAFM employs a multi-agent system following the principles of subsumption architecture (Brooks 1991). Over 70 agents are organized in a layered structure. The agents operating in the lower layers are responsible for managing basic reactive behaviors. For example, the road network agent constantly monitors the current positions of traffic participants from the time-series data supplied by the traffic manager. This allows it to continually assess and determine the specific lane segment that each traffic participant occupies. Higher layers manage more complex tasks through the integration and interpretation of outputs from lower layers. For instance, the overtake explainer agent uses information gathered from various other agents like the lane change agent and determines what mistakes the student made during an overtake maneuver and also what they did well.

The agent system operates within a game loop-style execution process, with some computationally heavy agents running in parallel on their own threads. These agents interact with and modify the knowledge graph, enabling effective communication, coordination, and collaboration.

The RTAFM primarily utilizes rule-based agents to monitor and evaluate student behavior. However, the gaze estimation agent is machine learning-based, leveraging a convolutional neural network in a computer vision task to track the student's attention, such as focusing on mirrors or blind spots.

Every driving situation encountered by the student is logged within the knowledge graph by the respective agent, including detailed performance metrics. If any driving mistakes occur, they are flagged as so-called alerts. For instance, when a student exceeds the speed limit, the Speed Compliance Agent registers an alert in the relevant driving situation node.

Both the Tutoring Agent and the Decision Support Agent actively monitor these driving situation nodes in the knowledge graph. While they are depicted as separate components in Figure 1 for clarity, they are integral parts of the agent system.

The Decision Support Agent acts as an interface between the system and human instructors, relaying real-time data from the knowledge graph to the teacher panel. This provides human instructors with up-to-date insights into the student's performance and areas of concern. As a result, instructors can offer specific, targeted feedback without the need for continuous observation. This not only facilitates a more efficient teaching process but also better equips instructors to address any questions or challenges the student might present.

The Tutoring Agent adopts a multifaceted approach. Engaging with the student through a multimodal interface (Philippe et al. 2020) which encompasses text, visuals, and audio. The tutoring agent autonomously determines the nature, timing, and modality of feedback. This decision-making takes into account both the student's cognitive load and the importance of delivering timely, relevant feedback.

While the RTAFM focuses on real-time assessment and feedback, understanding a student's driving abilities in-depth requires a more analytical approach, which is where the student model comes into play.

Student Model: Leveraging the knowledge graphs stored from each driving session, the student model provides a comprehensive and evolving understanding of a student's driving abilities over time. This model is rooted in the principles of Bayesian networks (Pearl 1985) and uses the knowledge graphs to update the student's skill progression after each driving session. This student model harnesses a Bayesian network to map out causal interconnections between different driving skills. These skills capture the intricate causal relationships between distinct driving maneuvers, such as overtaking, lane change, and turn signaling. Built in collaboration with professional driving instructors, this skill network discerns both composite and atomic skills. For instance, while the overtake skill is a composite skill, encompassing other abilities like lane change and safe following distance, turn signaling is considered an atomic skill.

Currently, the student model comprises 165 distinct skills, with each skill potentially having up to nine causal connections with other skills. Bayesian networks, renowned for their versatility across domains like artificial intelligence and risk analysis, harness Bayes' theorem to represent conditional dependencies between variables. By adeptly handling uncertainty and modeling intricate interrelations, they predict outcomes—even with incomplete data—based on observed evidence (Murphy 2012).

In our system, we work with two types of variables: directly measurable *evidence* graded from A-F, and latent *skill mastery* variables with states—mastered, learning, or struggling. We use Bayesian inference to predict skill mastery based on performance evidence. The Conditional Probability Distributions (CPDs) are derived from datasets generated by knowledgeable driving instructors, rather than purely heuristic approaches. To depict progress, we convert the posterior beliefs of skill mastery into percentages.

In the absence of prior data, every student is initially perceived as someone with average driving skills, sampled from our student population. This means all skill mastery nodes adopt the prior values based on the Parent-Children CPDs. However, post the initial driving session, the system possesses some insights about the student via its posterior probabilities. Leveraging this information, the student model assimilates these posteriors as transferred knowledge, incorporating this knowledge into the subsequent inference step after the next driving session.

Teacher Station and Teaching 1-to-N

The Teacher Station, acting as the central hub for the teachers, changes traditional driving instruction by enabling an instructor to manage multiple students concurrently. This capability is made possible via a WebRTC-based web interface, which allows the instructor to monitor each student's progress in real-time, irrespective of the physical location of the simulators.

In this integrated system, individual Teacher Panel views are generated locally at each simulator, offering detailed insights into the ongoing driving performance and specific mistakes of a student. These panel views effectively constitute real-time evaluative snapshots of each student's driving session.

Simultaneously, these Teacher Panel views are streamed to the teacher station, providing an assembled and comprehensive overview of all concurrent driving sessions. Thus, the teacher station serves as a central dashboard, presenting a real-time stream from each student's simulator, further enriched with a timeline of their performance.

The streaming solution forms the essential communication bridge linking the teacher station, the driving simulators, and a web server. This web server manages the list of available simulators that the teacher station can access and serves up the teacher view frontend, thereby enabling a comprehensive view of each student's driving session.

Teacher Panel

The Teacher Panel serves as a vital tool for instructors monitoring their students' driving sessions. It was collaboratively designed with input from teachers, UI experts, and AI researchers. A screenshot of the Teacher Panel during a driving session is shown in Figure 3. This intuitive interface offers comprehensive, real-time insights into student performance, neatly structured in a top-down format:

- **VDI Performance Assessments**: At the top, the panel displays a performance timeline, reflecting the student's actions and reactions in different driving situations. This includes performance scores for particular scenarios such as recent intersections, along with a concise list of any mistakes made during the last two minutes of driving.
- **Traffic Signs**: Next, a chronological display of the traffic signs passed by the student helps instructors understand the student's navigation and response to road rules.
- **Mirror and Signal Checks**: The panel also visualizes whether the student correctly checked all necessary mirrors and signaled appropriately before making lane changes and when turning at intersections. Additionally, it indicates if the student conducted regular rearview mirror checks, which they are advised to do at least every 10 seconds. Icons linked with specific timeline events represent this information for easy comprehension.
- **Speed and Pedal Usage Graphs**: The final section of the panel features graphs showing the student's speed and pedal usage over time, providing a quick overview of

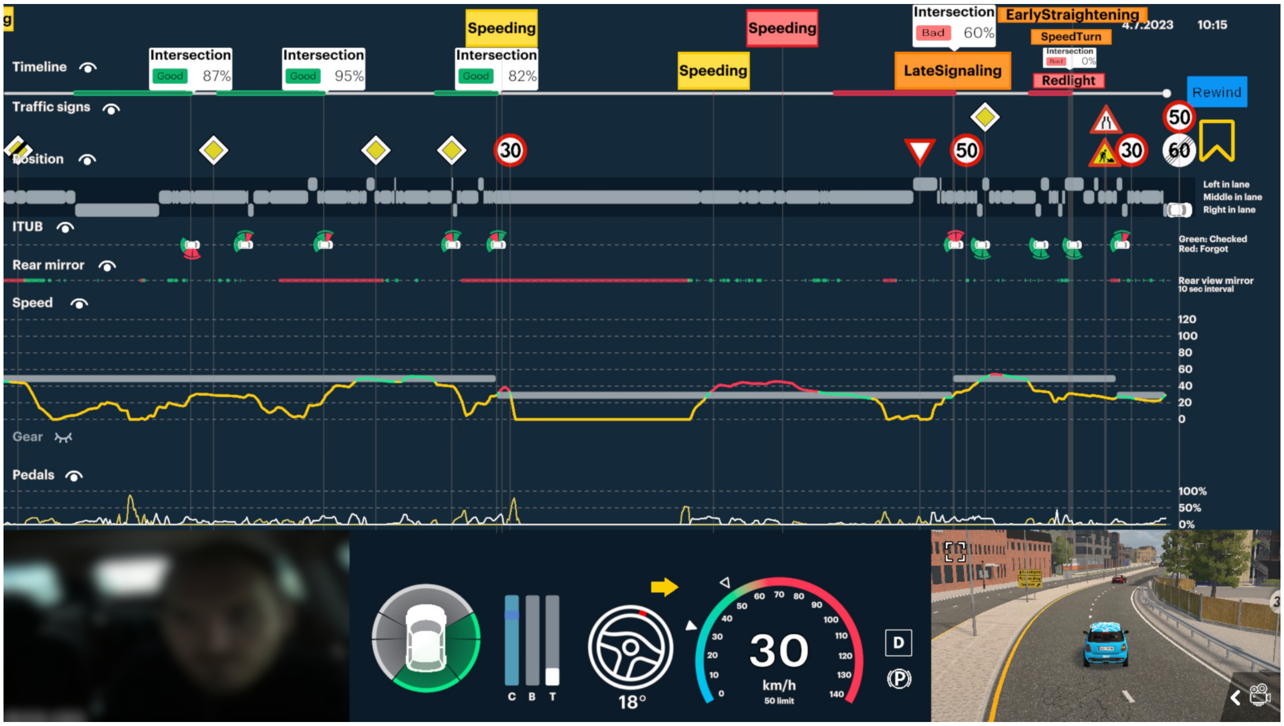

Figure 3: Teacher Panel screenshot featuring a chronological display of past driving events alongside real-time driving activity. The concurrent video feed captures the student's facial reactions (blurred in this image for privacy).

their control and responsiveness to varying driving conditions.

- **Live Visual Feeds**: In addition to the timeline and graphical data, the panel displays a live feed of the student driving in the simulator environment, accompanied by a real-time feed from a camera capturing the student's face. This visual context further enhances the instructor's understanding of the student's real-time reactions and overall performance.

The idea is that teachers focus on the top part of the teacher panel which gives an overview of the performance and mistakes in all situations. If teachers see some issue, they can delve deeper into the details given by the rest of the teacher panel and react accordingly, e.g. by talking directly to the student. All the information, apart from the live visual feeds, is sent by the VDI's decision support agent.

To illustrate, if a student drives too close to the car ahead, the student will hear an audio message from the tutoring agent stating, "You are too close to the vehicle in front." Simultaneously, the teacher will receive a concise alert from the decision support agent, displayed as "Distance" in a prominent alert box at the top of the timeline on their panel. Due to their training, teachers can instantly comprehend the implications of this brief message.

Overall, the combination of the Teacher Station and the individual Teacher Panels provide a detailed yet easily digestible snapshot of each student's performance in the simulator, allowing instructors to swiftly assess and guide their learning process. This structured setup ultimately ensures that the instructors can efficiently manage multiple students simultaneously, thus revolutionizing the traditional driving instruction process.

Mobile Application

Our dedicated smartphone application serves a dual purpose: allowing students to book new lessons and providing access to a detailed summary of their skill progression after each session. The feedback is derived from the student model of the VDI.

The user interface of the application is designed for clarity and ease of use. In the main skill progress view, the application displays an overview of the student's current skills in areas such as technical skills, traffic skills, environmentally friendly driving, and risk perception. Figure 4 depicts this high-level skill presentation within the mobile application.

For a more detailed analysis, students can explore individual skill categories. By selecting a specific high-level skill, they can access insights about their performance in related sub-tasks. Figure 5 provides an example of this, illustrating an evaluation of technical skills. This category includes specific skills such as 'normal braking', which assesses the student's ability to brake smoothly.

Overall, the mobile application bridges the gap between the driving simulator sessions and the students. It not only offers direct insights into their performance but also helps them identify areas that require further practice and improvement.

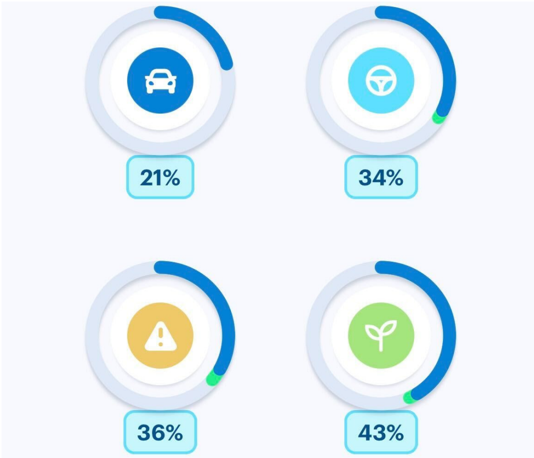

Figure 4: Snapshot of the top page from the Way smartphone application's student model summary. It showcases the four primary aggregate driving skills: Technical Skills, Traffic Skills, Environmentally Friendly Driving, and Risk Perception. Skill improvement since the last session is highlighted in green within the circular rings

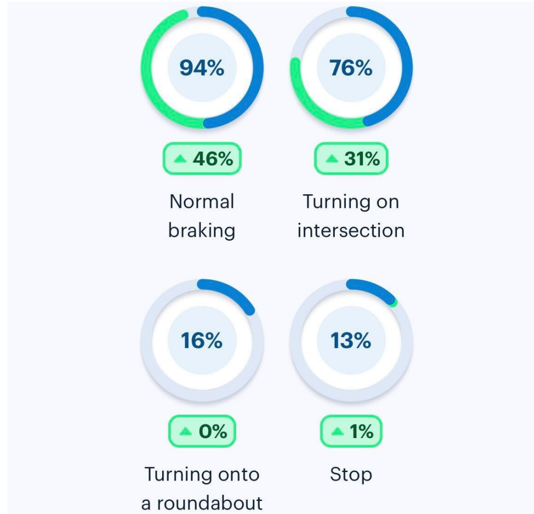

Figure 5: Excerpt showing the progression of four technical skills. Percentages in circular rings represent mastery level. The numbers below depict the delta in skill improvement from the last session, also highlighted in green within the circular rings. Note: This represents a subset; the full model comprises many more technical skills.

Deployment

The deployment of our VDI along with the driving simulators represents a significant step forward in driver education.

The driving simulators, equipped with the VDI, have been installed in 5 simulators at 3 different locations of a commercial driving school called Way AS in Norway. The VDI together with the live streaming solution has been deployed since June 2021 in all of the simulators. The decentralized nature of the simulators, combined with the centralized teacher station, allows for an innovative approach to driver training, making it possible for a single instructor to monitor and guide multiple students simultaneously.

The system facilitates parallel training for up to five students under the guidance of a single instructor, which dramatically decreases the cost of driving education, given the significant portion of expenses dedicated to instruction.

Since its inception, the system has proven both scalable and effective, serving a substantial number of students. Specifically, in 2022, 623 students underwent simulator-based training for the Category B driving license, the standard car license in the European Economic Area (EEA). The VDI's real-time feedback and the detailed performance timeline at the teacher station have both played pivotal roles in enhancing the students' learning experience and improving the efficiency of the teaching process.

User Feedback on the Virtual Driving Instructor

Student Experience Survey Results

Between February and April 2023, we carried out a survey to gather insights into the students' experience with the simulator and the VDI. Students took the survey immediately after each simulator session. The questionnaire had eight questions in total. We collected a total of 316 responses from 87 unique students. Students took multiple driving sessions and contributed repeated feedback after each lesson.

As illustrated in Figure 6, the simulator provided a positive experience for a vast majority of students. Specifically, 74% of simulator sessions were rated as good or very good. Regarding the VDI's feedback, over half of the students found it comprehensible, as shown in Figure 7. Less than 5% of students struggled to understand the feedback given. When assessing the level of agreement with the VDI's feedback (Figure 8), 55% of students partially agreed with the given suggestions, while 32% fully agreed. Conversely, only 10% disagreed with the feedback received.

In-Depth Student Interviews

To delve deeper into the perceived effectiveness of the deployed system, we supplemented our research with targeted interviews involving a subset of students who had utilized the simulators. Importantly, all interviewees had attended at least six simulator lessons prior to the interview, ensuring they had sufficient experience with the system.

We asked each participant the same 15 questions. It was divided into questions regarding the experience in the simulator with the VDI and experience with the app. The goal of these discussions was to obtain first-hand feedback regarding their experiences with the VDI and the simulator environment. These interviewees were randomly selected from the pool of 87 students who participated in the survey.

Out of ten students approached, we conducted full interviews with six. One of the ten was part of a pilot interview which helped us refine our interview guide. The remaining

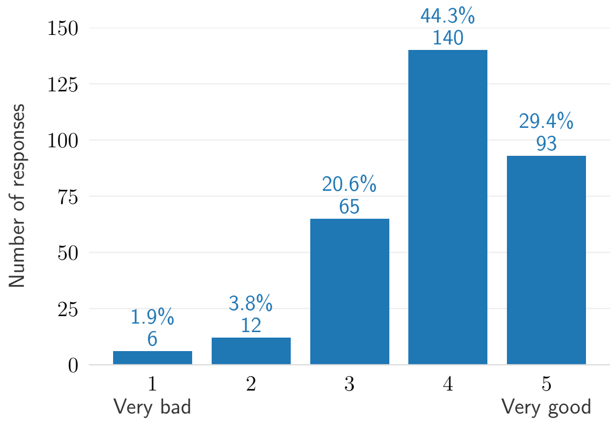

Figure 6: How would you rate your last simulator session experience on a scale of 1-5?

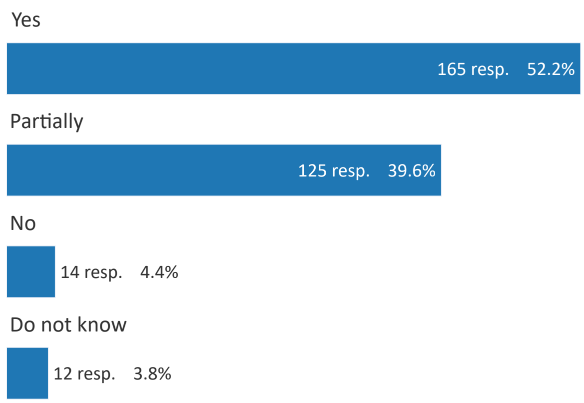

Figure 7: Did you find the feedback you received from the VDI during the simulator session to be understandable?

three students were either unavailable or declined to participate.

Please note that all interviews were conducted in Norwegian for the comfort and convenience of the students. Any specific responses referred to in this document are translations into English for the sake of clarity and accessibility. The same interview guide was consistently used across all interviews to ensure a standardized and comparable approach.

The initial query focused on whether the feedback provided by the VDI was perceived as confusing or frustrating by the participants. Out of the six interviewees, five found the feedback mostly helpful. For instance, the third student estimated that the advice was accurate 80-90% of the time as per his perception. The second student reported that the feedback was instructive and didn't cause any frustration. However, she experienced motion sickness, limiting her driving sessions to 30 minutes each.

Despite the generally positive responses, some disagreement arose. On occasion, students anticipated negative feedback for their mistakes and were taken aback when none

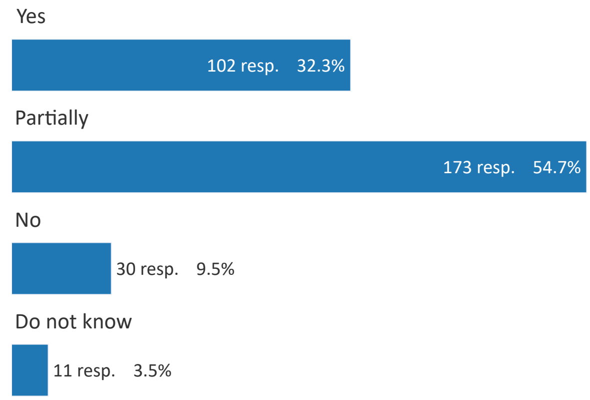

Figure 8: Did you agree with the feedback you received from the VDI during the simulator session?

was provided. The system is designed to avoid continuous criticism to prevent overwhelming the students, even if the errors are logged. This highlights a valuable insight for our team: we need to find a way to convey this approach to the students to maintain their trust in the system. One possible solution could involve an explicit explanation that mistakes are still recorded, even if no immediate feedback is given. Alternatively, we might consider providing a subtle visual cue when an error is logged, avoiding the disruption caused by extended auditory feedback.

Two primary categories of disagreement were noted. The first involved feedback on the use of turn signals at intersections and roundabouts, and the second centered on mirror-checking procedures. The current limitations of the eye-tracking system were a primary concern, given its inconsistency and therefore unreliability in detecting mirror-checking.

On the topic of turn signaling, it's clear that our briefings and explanations require improvement. For example, student three stated, "I signaled right even though I was taking the roundabout. I was told it was wrong, but I'd like to know why." This feedback highlights a need for more detailed instruction about signaling rules in roundabouts. According to Norwegian rules, drivers should signal left before entering the roundabout if they intend to exit left or continue around to the opposite side. This particular point appears to have caused some confusion, indicating that our briefing videos need to more explicitly explain these regulations.

Moreover, there's an additional complexity concerning the automatic cancellation of turn signals, a feature present in most cars, which depends on the change in the steering wheel angle. Occasionally, this function may terminate the signal prematurely, without the students noticing. This can cause confusion and misunderstandings, which suggests a two-fold action plan for us: first, ensure that the VDI recognizes when the car has automatically shut off the turn signal; second, adjust the VDI's feedback accordingly. By addressing these issues, we hope to enhance our system's clarity and instructional effectiveness.

Another point of contention was raised by student five, who disagreed with the VDI's feedback on his timing of turn signaling. We require students to initiate turn signaling at least five seconds before reaching an intersection. This is notably earlier than most drivers would typically signal, yet it aligns with Norwegian driving education. Therefore, a more detailed briefing is required to clarify this rule.

The only lesson currently providing such detailed briefing during the session is the "night driving" module, which student three singled out for praise. He reported enjoying the clear instructions provided during the intermittent stops.

When asked about their preferred type of feedback, the majority of participants voiced a clear preference for audio feedback over text feedback displayed on the in-car dashboard. This preference is logical given that students' attention is primarily directed towards the road, limiting their ability to read dashboard text. Students 4 and 5 mentioned that they didn't notice the dashboard feedback at all. While most students appreciated the audio feedback, Student 3 critiqued the voice for its lack of human-like qualities, describing it as "flat". It's worth noting that the voice used for feedback is an AI-generated voice.

Upon inquiry about whether the feedback facilitated error recognition and correction, the unanimous response was affirmative. For instance, Student 1 highlighted how the system alerted her to speeding and improper steering during turns. However, Student 4 shared mixed experiences, stating that while the feedback generally helped, there were instances where she disagreed with the system's remarks.

When queried if they wished for more detailed feedback, opinions were split: half of the participants found the current level sufficient. Specifically, Student 2 desired more instructions for roundabout navigation, while Student 3 suggested less repetitive and more varied feedback.

The final question, which addressed the desire for more positive reinforcement, elicited diverse responses. Two participants believed the balance between positive and negative feedback was appropriate. Student 5 expressed a desire for more frequent positive feedback to validate correct actions, whereas Student 4 felt positive feedback was unnecessary, assuming the absence of feedback implied correct actions. Student 3 found the positive feedback less genuine, particularly when it immediately followed criticism.

We additionally solicited feedback regarding the user experience of the mobile application, specifically focusing on the experimental feature of displaying skill progression. Notably, Students 4 and 5 voiced concerns over the accuracy of the presented data, leading to some mistrust in the numbers. Conversely, Students 3 and 6 expressed satisfaction with the numerical representation, finding that it aligned well with their perceived performance.

In terms of understanding their progression in driving skills, the majority of students confirmed the app's utility to varying degrees. Particularly, the application proved beneficial in highlighting areas for improvement. Despite occasional discrepancies in data, several students appreciated the app's intuitiveness and clarity in the presentation of feedback. For instance, Student 3 articulated that the app effectively depicted his current skill level, suggesting improvements, and underscored its intuitive usage.

The deployment so far has revealed both the impact and problems of the VDI system in a real-world setting. These insights will guide our system's future enhancements.

Conclusion and Future Work

The introduction of our VDI system marks a significant advancement in the realm of driver education. By interfacing with high-fidelity driving simulators, the VDI provides a unique learning experience for students, offering immediate, personalized feedback and enhancing overall learning outcomes. Furthermore, the innovative setup allows for an efficient teaching process, as instructors can monitor and guide multiple students simultaneously, regardless of the students' physical location.

The deployment of the system has been successful, with a significant number of students actively using the setup. Preliminary feedback from students has been generally positive, highlighting the effectiveness of the system in improving their driving skills and the efficiency of their learning process.

Despite these promising results, we acknowledge that this is just the beginning. Further refinements to the system can be implemented based on ongoing feedback from students and instructors. We also recognize the need for a more comprehensive evaluation of the system's impact on students' on-road driving performance, which could be a direction for future research. Additionally, there is a requirement for more extensive and personalized briefing about rules and correct behavior in traffic, especially during lessons.

Our long-term strategy involves implementing a feature that will allow students to revisit specific segments of their driving sessions that are particularly instructive. This will not only highlight their common errors but also underscore the aspects they have executed proficiently.

Leveraging the recent advances in chatbot technology (Brown et al. 2020), a compelling avenue for future enhancement is the integration of an interactive chatbot tailored for drivers' education. Equipped with speech recognition and synthesis, it would enable two-way communication between the VDI and students. This allows students to actively engage, seek clarifications, and request guidance, simulating a traditional instructor-student dynamic in a digital environment.

In conclusion, our work contributes to the evolving field of AI in education, demonstrating how advanced technologies can significantly enhance traditional educational models. We look forward to seeing the VDI system further evolve and impact the future of driver education.

Acknowledgments

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