
Towards a Human-Centric Taxonomy of Automation Types

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Abstract

A human-centric, consumer-facing automation taxonomy is proposed to address emergent issues of consumer confusion related to automation types and associated role responsibility. A set of surveys were fielded to help understand the extent to which consumers were able to accurately interpret a proposed consumer-facing taxonomy relative to the 6-level SAE J3016 taxonomy. Results show a mixed benefit of the proposed set compared to the J3016 set. Overall, across both taxonomies, consumers were best able to differentiate the extremes of automation types, leading to the question of whether or not it may be beneficial to provide a simplified representation of automation types to communicate functionality. A binary framing (“driving” vs. “riding”) is proposed to ensure consumer understanding. This framework may best serve consumer understanding until such time as educational or other efforts can be developed and tested to ensure consumers have the needed understanding to make informed decisions around the safe and effective use of vehicle automation.

Introduction

A key human-related issue within vehicle automation concerns the degree of human engagement required to maintain safe control, either as an operator, monitor, supervisor, or passenger. To act appropriately in these roles, the human must have a clear understanding of his/her responsibilities at any given moment of time. These responsibilities change based on the type of automation engaged (SAE J3016, 2018).

Recent research indicates that consumers are often confused about the capabilities of deployed forms of vehicle automation due to role confusion, misattributing greater role responsibility to

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automation based on technology naming alone (Abraham et al., 2017). Perceptions of automated system capabilities are further inflated based on media reports and individual tendencies to adopt new forms of technology (Lee et al., 2018).

Within a wide range of global regulatory organizations, there are several ongoing proposals that are intended to clearly characterize driver responsibilities (UNECE R79 ACSF; Campbell et al., 2017; Euro NCAP). A goal of these efforts is to define adequate driver engagement based on automation type, with the intent of clearly articulating the human's role across automation types in a manner that is accurately understood by the general public.

This document proposes a human-centric, consumer-facing automation type taxonomy. The rationale for the taxonomy follows in part from empirical results (reported here) of consumer success in correctly interpreting both current SAE engineering-oriented terminology and a range of alternate terms intended to be more "lay-user" oriented. The resulting empirical findings suggest the need for an overarching approach to managing the communication problem. In the end, the proposed taxonomy simplifies the framing of automation in terms of its implications to the human's role as either "driving" or "riding" in order to address a number of issues:

- Implications of automation's introduction to human responsibility
- Oversimplified function allocation of the primary driving subtasks to human or technology
- Consumer confusion with a 6-level taxonomy.

Issues to Resolve in Proposing a Consumer-Facing Automation Taxonomy

Implications of automation's introduction to human responsibility

When automation is introduced into a dynamic task environment like in driving, *additional tasks* are also introduced that the human is responsible to perform (Wickens & Kessel, 1981; Bainbridge, 1983; Cook et al., 1990). Performing a task within a dynamic environment introduces complexity and uncertainty into the human-automation interaction. Still part of the overall system, the human cannot complacently relegate tasks to automation. New skills are required in the role of a supervisor.

Supervision of automation in a dynamic, uncertain environment involves information integration and analysis, system expertise, analytical decision-making, sustained attention, and maintenance of manual skill (Bhana, 2010; Casner et al., 2014). These supervision skills can be summarized as follows:

- Information integration & analysis:
 - Quickly and accurately interpret potentially high volumes of automation-generated data in real-time
 - Extract useful information from provided HMIs that may vary in workload depending on design characteristics of the HMIs

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- System expertise
 - Develop expertise on situation-dependent functionality and performance of different automated technologies
- Analytical decision-making:
 - Evaluate computed solutions provided by automated systems
 - Based on context, decide either to stop automated control or allow it to continue
- Sustained attention:
 - Combat boredom and fatigue to maintain active monitoring of low-level system control information during routine automated tasks
- Manual (i.e., driving) skill:
 - Continue to practice and maintain manual (i.e., driving) skills

It is from competently performing this set of new skills that the human is able to effectively troubleshoot and recover if the automation fails or if something unexpected happens which requires human intervention (Onnasch et al., 2014; Wickens et al., 2010).

In framing automation types, there are two distinctly different perspectives: a “levels-of-automation” or “who does what” perspective, and a “coordination of automation and people” or “how to work together” perspective (Lee, 2018). A levels of automation (LoA) perspective arises from a function allocation approach, in which tasks or pieces of tasks that were once assigned to people are reassigned to automation. In this view, a task such as driving is broken down into subtasks that are divided between a human and automated system, in which the focus is on a single human-automation unit. In driving, for example, a LoA perspective is constrained to interaction between the driver and an automated system such as adaptive cruise control (ACC). A “coordination of automation and people” perspective considers the network of agents involved in a larger human-automation-environment unit, where there are layers of connections between independent elements of automation within the primary system, forms of multimode automation, and links to people and automation outside the primary system (Woods, 2016). In driving, this network would include the driver and automation types inside the vehicle, as well as other road users, external operators, and forms of automation outside the vehicle (Lee, 2018). It has long been understood that education around these new roles – introduced by the addition of automation into a task domain – is critical to the effective and safe use of automated systems (Prinzel et al., 2001; Bailey & Scerbo, 2008).

In applying a “coordination of automation and people” perspective to driving, the task is conceptualized not as one to be subdivided into parts that are assigned to either the human or automation, but as a coordination and collaboration activity between these two agents with the goal of together achieving safe driving in a dynamic environment. A primary insight from this perspective is that placed within the context of a dynamic environment, machine performance is brittle without a human supervisor to oversee and coordinate its performance (Bradshaw et al., 2013).

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The current conversation within industry, policy organizations, and in academia on forms of vehicle automation is currently guided by a LoA perspective defined by six levels (SAE, J3016, 2018). As framed within this taxonomy, for Level 0 – No Driving Automation, the human is solely responsible to control lateral and longitudinal direction of the vehicle, monitor the environment, monitor vehicle performance, and respond in an emergency. For Level 1 – Driver Assistance, the human is responsible to control the lateral direction of the vehicle if ACC is engaged or the longitudinal direction of the vehicle if lane centering is engaged, monitor the environment, monitor vehicle performance, and respond in an emergency. The vehicle’s automated technologies are responsible to control the longitudinal direction of the vehicle if ACC is engaged or the lateral direction of the vehicle if lane centering is engaged. For Level 2 – Partial Driving Automation, the human is responsible to monitor the environment, monitor vehicle performance, and respond in an emergency. The vehicle’s automated technologies are responsible to control the longitudinal and lateral direction of the vehicle. For Level 3 – Conditional Driving Automation, the human is responsible to take over control of the vehicle if the automation requests the driver to intervene, and to respond in an emergency. The vehicle’s automated technologies are responsible to control the lateral and longitudinal direction of the vehicle, and to monitor the environment. For Level 4 – High Driving Automation and Level 5 – Full Driving Automation, the vehicle’s automated technologies are solely responsible to control the longitudinal and lateral direction of the vehicle, monitor the environment, and respond in an emergency, within a limited operational design domain (ODD) for Level 4, and without limit to the ODD in Level 5. The driver’s responsibilities per Level are summarized in Table 1 under the set of columns shaded in gray: “Brake & Accelerate”, “Steer”, “Monitor the Environment”, “Monitor Vehicle Performance”, and “Respond in an Emergency”.

This function allocation of vehicle control tasks does not consider the supervision tasks added to the set of human responsibilities per Level. The second set of columns shaded in yellow in Table 1 list the set of supervision responsibilities each Level introduces: “Monitor Automation Performance”, “Respond to Vehicle Messages (i.e., those issued by the automated system requesting the human to take back control of the vehicle), and “Decide on Automation Use Based on ODD”. The implications of Table 1 for the added responsibilities automation introduces is that there is a supervision cost for all except the highest level of automation, in which it is deemed in full control for all driving environments. (Notably, even at this level, it is expected that there may be human supervision in some capacity, though, distinctly, located *off-board* the vehicle.)

Breaking apart the driving task into subtasks, without specifying which subtasks are interdependent, presumes the driver is capable of performing only part of the whole task without a performance cost (e.g., without a decline in the rate and extent of monitoring). The next section discusses why this assumption is problematic.

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Table 1. SAE Levels of Automation Taxonomy Based on Driver Role

SAE (J3016, 2018)	Driver's Role							
	Vehicle Control Tasks*					Supervise Automation*		
	Brake & Accelerate	Steer	Monitor the Environment	Monitor Vehicle Performance	Respond in an Emergency	Monitor Automation Performance	Respond to Vehicle Messages	Decide on Automation Use Based on ODD
Level 0: No Driving Automation	X	X	X	X	X			
Level 1: Driver Assistance	X		X	X	X	X	X	X
		X						
Level 2: Partial Driving Automation			X	X	X	X	X	X
Level 3: Conditional Driving Automation					X		X	X
Level 4: High Driving Automation								X
Level 5: Full Driving Automation								

* When automation has been engaged and is active

Oversimplified function allocation of the primary driving subtasks to human or technology

A levels of automation perspective presumes it is possible to break apart the driving task into subtasks that can be wholly allocated to either the human or the automation. In practice, driving subtasks do not neatly parse into longitudinal control, lateral control, and object detection and response (OEDR) (Seppelt et al., 2017). Driving involves operational (moment-to-moment vehicle control), tactical (intermittent object and event detection and vehicle maneuvering), and strategic (navigation) tasks, which are temporally and hierarchically dependent on one another, and all of which require driver monitoring (Merat et al., 2018).

Binary function allocation does not cleanly classify Level 1 and Level 2 automation types. For these Levels, automated systems perform braking/accelerating tasks (ACC) and/or lane centering. In practice, neither the system nor the driver fully controls the vehicle’s longitudinal and/or lateral movement because OEDR (the driver’s responsibility for these levels) is **both** an operational and a tactical activity (i.e., “R” in “OEDR” requires the driver’s steering/braking input). Simply, in performing “OEDR” for these Levels, the operator is also executing “lateral and longitudinal movement”; and, in performing “lateral and longitudinal movement”, the automated system is also partially performing “OED”.

Binary function allocation also results in an oversimplification of driver monitoring requirements for Levels 2 and 3. Separating monitoring from vehicle control presumes the driver can effectively respond when s/he is requested to perform the fallback task (Level 3), and/or is able to monitor at sufficient rate and breadth to detect the presence of a silent system failure (Level 2 & 3). In the way the driving task is currently temporally structured, the driver is expected to remain coupled to moment-to-moment vehicle control performance to effectively perform

“OED” at the same rate and breadth of scanning as when driving manually (Merat et al., 2018). The simple implication is that for a Level 2 and 3 system, monitoring cannot be decoupled from moment-to-moment vehicle control feedback without a loss of engagement and consequent decrement to driver response in fallback conditions (Victor et al., 2018). Drivers need to provide collaborative steering input to effectively remain in-the-loop for these Levels (Flemisch et al., 2014), and/or the moment-to-moment control feedback needs to be reinstated through continuous HMI (Seppelt & Victor, 2016; Seppelt & Lee, Submitted). Such measures directly support the driver’s added supervisory tasks listed in the previous section. Simply, for humans, object and event detection, and readiness for response (i.e., receptivity—part of the fallback task in Level 3) are both forms of monitoring that are directly tied to operational control; they cannot be cleanly separated as exclusive driving subtasks to allocate to the driver.

These limitations of function allocation call for a need to designate a classification of automation that does not break driving into multiple subtasks. Instead, a simple identification of forms of automation that require the driver to remain engaged in some aspect of driving are recommended to be designated from those that do not require driver engagement. “Driving” and “Riding” are two proposed terms to separate out those technologies that are designed with the expectation of a driver in the driver’s seat from those that are meant to operate without a driver present in the vehicle, respectively.

Consumer confusion with a 6-level taxonomy

The previous two sections discuss a number of identified issues that emerge from a multi-level taxonomy of automation types as “levels”. Implications of automation’s introduction to human responsibility, including oversimplified function allocation of the primary driving subtasks to human or technology, are documented. Consumer confusion around important but complex descriptions of six levels of automation, written by engineers for engineers, further complicates general interpretation.

As such, the authors, with consultation from other stakeholders, developed a proposal for a consumer facing automation type taxonomy (see Table 2). In this taxonomy, a short definition and primary purpose was defined, along with a designation per level of “who” is primarily responsible for safety, and if the human is free to engage in non-driving related activities. The hierarchy of the taxonomy is a simplified designation of “driving” and “riding”. This framing was proposed to communicate automation types to consumers based upon “who” (between human and automation) was responsible for safety. A simplified framing in these terms addresses the issues raised in the previous two sections on tasks automation introduces, and with function allocation.

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Table 2. Consumer-Facing Automation Type Taxonomy

Human's Role	Automation Type	Definition	Primary Purpose	Primary Responsibility for Safety	Human Is Free to Engage in Non-Driving Related Activities
Driving	Safety Assistance	Momentary intervention(s)	Enhanced safety	Driver	No
	Driver Assistance	Human and technology each perform part of the driving task	Convenience and potential enhanced safety	Driver	No
	Supervised Driving	Automated driving system that requires human supervision	Convenience and potential enhanced safety	Driver	No
	Autonomous Test Vehicle	Self-driving vehicle that requires professional human supervision	Testing	Driver	No
Riding	Intermittent Self-Driving	Technology performs all of the driving task for a limited set of use conditions	Enhanced safety and convenience	Vehicle	Yes (only when in autonomous mode)
	Driverless	Technology performs all of the driving task for entire trips	Enhanced safety, convenience and mobility	Vehicle	Yes

While the taxonomy presented in Table 2 offers heuristic refinements from a human factors oriented perspective, the question remained as to whether it alone provides meaningful improvement in public understanding. This section describes a set of surveys fielded to help understand the extent to which consumers were able to accurately interpret the proposed consumer-facing taxonomy relative to the 6-level SAE J3016 taxonomy. The surveys were also used to evaluate the usefulness of alternate names associated with automation type. Overall, we aimed to determine if consumers understand key diverging characteristics between automation types without in-depth education. The following section describes the surveys, sample, and results.

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Table 3. Set of Terms and Accompanying Definitions Tested in Levels of Automation Survey

Term Set 1	Term Set 2	Term Set 3	Definition	SAE J3016 Term Set	Definition
Safety Assistance	Intervention Technology	Momentary Intervention	Technology that provides momentary intervention(s) to vehicle control (e.g., emergency braking) to enhance safety	No Driving Automation	The driver performs the entire dynamic driving task, even when enhanced by active safety systems.
Driver Assistance	Assisted Driving	Driver Assistance	The human and technology each perform part of the driving task (accelerating, braking, and monitoring all road and vehicle conditions) to increase convenience and to potentially enhance safety	Driver Assistance	Technology that performs the sustained and operational design domain-specific execution of either the lateral OR the longitudinal vehicle motion control subtask of the dynamic driving task (but not both simultaneously) with the expectation that the driver performs the remainder of the dynamic driving task.
Supervised Driving	Supervised Driving	Supervised Driving	Technology that performs all of the driving tasks (accelerating, braking, and monitoring all road and vehicle conditions) but that requires human supervision to increase convenience and to potentially enhance safety	Partial Driving Automation	Technology that performs the sustained and operational design domain-specific execution of both the lateral and longitudinal vehicle motion control subtasks of the dynamic driving task with the expectation that the driver completes the object and event detection and response subtask and supervises the technology.
Self-Driving Test Vehicle	Self-Driving Test Vehicle	Self-Driving Test Vehicle	Technology that performs all of the driving task (accelerating, braking, and monitoring all road and vehicle conditions) but that requires professional human supervision for testing purposes	Conditional Driving Automation	Technology that performs the sustained and operational design domain-specific entire dynamic driving task with the expectation that the dynamic driving task fallback-ready user is receptive to technology-issued requests to intervene, as well as to dynamic driving task performance-relevant system failures in other vehicle systems, and will respond appropriately.
Intermittent Self-Driving	Conditional Self-Driving	Part-Time Self-Driving	Technology that performs all of the driving task (accelerating, braking, and monitoring all road and vehicle conditions) for a limited set of use conditions (e.g., highway only) to enhance safety and convenience	High Driving Automation	Technology that performs the sustained and operational design domain-specific entire dynamic driving task and dynamic driving task fallback without any expectation that a user will respond to a request to intervene.
Driverless	Full-Time Self-Driving	Autonomous Driving	Technology that performs all of the driving task (accelerating, braking, and monitoring all road and vehicle conditions) for the entire trip to enhance safety, convenience, and mobility	Full Driving Automation	Technology that performs the sustained and unconditional (i.e., not operational design domain-specific) entire dynamic driving task and dynamic driving task fallback without any expectation that a user will respond to a request to intervene.

Methods

Participants

Participants were recruited using online notices and web posts to the MIT AgeLab and New England University Transportation Center websites. The survey was open between July 6th and July 31st 2018. It was deployed three times to a unique set of individuals, once for each of the three sets of terms listed in Table 3. For the first two deployments, half of the sample received the set of SAE level of automation terms and definitions, the other half received the first and second proposed set of terms, respectively, and accompanying definitions. For the third deployment, the full sample received the third proposed set of terms and accompanying definitions. Figure 1 summarizes participant deployment, return rate per term set, and demographic composition of the analyzed sample.

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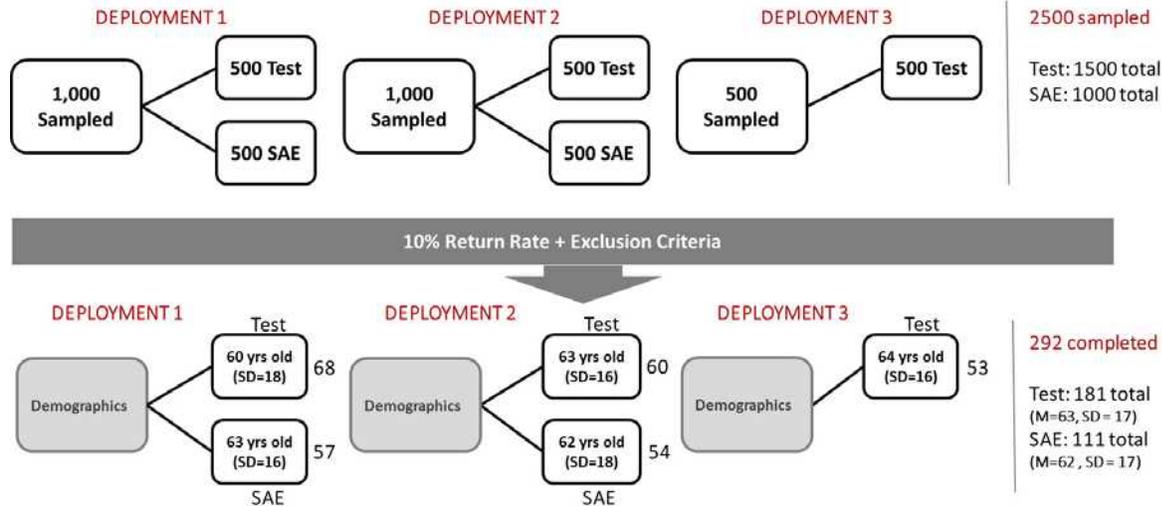


Figure 1. Participant deployment and composition showing mean age (and standard deviation).

In total, 292 individuals completed the survey. Responses were excluded from analysis if the respondent was not a licensed driver, did not own a vehicle, drove less than 1 day per week, had less than 5 years of driving experience, or if s/he did not complete the full survey.

The age and gender breakdown for each of the three deployments per term type is summarized in Figure 1. The total sample had 181 individuals who completed the survey for the set of proposed terms and definitions, and 111 individuals who completed the survey for the comparison SAE term set and definitions; the mean age of respondents was 63 (SD = 17), and 62 (SD = 17), respectively.

Survey procedure and instrument

Participants were told in online instructions that the survey would take less than 10 minutes and would involve answering questions about words associated with vehicle automation. They were offered the opportunity to enter a raffle for one of ten \$50 Amazon gift cards if they completed the survey.

Each participant received a set of questions per automation type for the full set of 6 levels based on LoA taxonomy condition (proposed or “test”; SAE). The set of questions per automation type were the same, with the exception of the term and definition changing within the question’s wording. An example of this question set is shown in Figures 2 and 3 below. Per term and definition, the following questions were asked:

- **Question 1:** Say there was a vehicle described as having technology that [Automation type definition], on which this technology is termed [Automation type term]. From the provided definition of [Automation type term], which of the following driving tasks, if any, would you perform? (Please select all that apply)
 - Brake & Accelerate

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- Steer
 - Monitor the Environment
 - Respond in an Emergency
 - None of the Above
- **Question 2:** How well do you think this term [Automation term type] fits the description of the technology?
 - Not at all (1) ... Perfectly (7)
- **Question 3:** Are there any words or set of words missing or that you think would better describe this technology than [Automation type term]?
 - Yes
 - No
- **Question 4:** Please select 1-3 words from the set below that best describes [Automation type definition]:
 - Partial; Full; Part-Time; Full-Time; Intermittent; Continuous; Conditional; Redundant; Low; High; Shared; Delegated; Momentary; Sustained; Collaborative; Supervised; Assisted; Assistance; Support; Intervention; Automation; Automated; Driverless; Self-Driving; Driving; Driver; System; Vehicle; Feature; Other (please specify)

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Say there was a vehicle described as having **technology that performs the sustained and unconditional (i.e., not operational design domain-specific) entire dynamic driving task and dynamic driving task fallback without any expectation that a user will respond to a request to intervene**, in which this technology is termed "**Full Driving Automation**".

From the provided definition of "**Full Driving Automation**", which of the following driving tasks, if any, would you perform? (Please select all that apply)

 Brake & Accelerate	 Steer	 Monitor the Environment	 Respond in an Emergency	None of these
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How well do you think this term "**Full Driving Automation**" fits the description of the technology?

Not at all Perfectly

Are there any words or set of words missing or that you think would better describe this technology than "**Full Driving Automation**"?

Yes	No
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Figure 2. Example set of four questions administered per automation type term and associated definition (Page 1).

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Please select 1-3 words from the set below that best describes "technology that performs the sustained and unconditional (i.e., not operational design domain-specific) entire dynamic driving task and dynamic driving task fallback without any expectation that a user will respond to a request to intervene".

Partial	Shared	Automation
Full	Delegated	Automated
Part-time	Momentary	Autonomous
Full-time	Sustained	Driverless
Intermittent	Collaborative	Self-Driving
Continuous	Supervised	Driving
Conditional	Assisted	Driver
Redundant	Assistance	System
Low	Support	Vehicle
High	Intervention	Feature
Other (please specify)		
<input type="text"/>		



Figure 3. Example set of four questions administered per automation type term and associated definition (Page 2).

For each participant, the order in which the terms and associated definitions were administered per set of four questions were randomized. In total, each participant received 24 questions (6 automation types x 4 questions per type). Twelve additional questions were posed to collect demographic information, including age (two variants of this question were included to validate response), gender, and education, as well as an indication of familiarization with SAE and levels of automation, interest in automation and self-driving vehicles, field of employment, relevance of job to automotive industry, and zip code. The survey was constructed in Qualtrics and administered online.

Results

Two primary variables were analyzed from this survey to evaluate participant understanding and perception of automation terms and associated definitions: the first question per set assessed **accuracy** (“Say there was a vehicle described as having technology that [Automation type definition], on which this technology is termed [Automation type term]. From the provided definition of [Automation type term], which of the following driving tasks, if any, would you perform?”); the second question per set assessed **perceived fit** of the automation type term to its definition (“How well do you think this term [Automation term type] fits the description of the technology?”).

Accuracy was calculated on an integer scale from 0 – 5 based on a participant’s selection out of the five possible driving task options: 1) Brake & Accelerate, 2) Steer, 3) Monitor the Environment, 4) Respond in an Emergency, and 5) None of These. The correct selections per Level by LoA taxonomy condition are shown in Tables 4 & 5. For each of the five options per question, participants received a “0” if they did not correctly select/leave blank the option, and a “1” if they correctly selected/left blank the option. The five integers per question were summed to produce a total score out of five.

Table 4. Scoring Key for Question 1 Per Level for Proposed Automation Taxonomy

			Vehicle Control Tasks				
MIT_Set 1	MIT_Set 2	MIT_Set 3	Brake & Accelerate	Steer	Monitor the Environment	Respond in an Emergency	None of These
Safety Assistance	Intervention Technology	Momentary Intervention	X	X	X	X	
			X	X			
Driver Assistance	Assisted Driving	Driver Assistance		X	X	X	
			X				
Supervised Driving	Supervised Driving	Supervised Driving			X	X	
Self-Driving Test Vehicle	Self-Driving Test Vehicle	Self-Driving Test Vehicle			X	X	
Intermittent Self-Driving	Conditional Self-Driving	Part-Time Self-Driving					X
Driverless	Full-Time Self-Driving	Autonomous Driving					X

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Table 5. Scoring Key for Question 1 Per Level for SAE (J3016) Automation Taxonomy

SAE (J3016, 2018)	Vehicle Control Tasks				
	Brake & Accelerate	Steer	Monitor the Environment	Respond in an Emergency	None of These
Level 0: No Driving Automation	X	X	X	X	
Level 1: Driver Assistance	X		X	X	
		X			
Level 2: Partial Driving Automation			X	X	
Level 3: Conditional Driving Automation				X	
Level 4: High Driving Automation					X
Level 5: Full Driving Automation					X

Perceived fit was assessed with the raw score from the 0 – 7 Likert scale from the second question.

Accuracy

From the three proposed term sets, the term with the highest average accuracy rating for each type was selected for comparison with the SAE level terms. Table 6 shows the average, standard error, and N for each term per automation type. In the case of the selection of the Type 2 term, the average for the term in the second set (“Assisted Driving”) had a higher score than the average of the first and third sets (M=3.41), which used the same term (“Driver Assistance”); consequently, it was selected for comparison with the SAE levels.

Table 6. Mean Accuracy Scores for Proposed Term Sets

	Term Set 1			Term Set 2			Term Set 3		
	Mean	SE	N	Mean	SE	N	Mean	SE	N
Type 1 <i>Safety Assistance</i>	2.74	0.16	68	3.05	0.15	60	2.89	0.19	53
				<i>Intervention Technology</i>			<i>Momentary Intervention</i>		
Type 2 <i>Driver Assistance</i>	3.23	0.11	65	3.52	0.09	58	3.60	0.09	47
				<i>Assisted Driving</i>			<i>Driver Assistance</i>		
Type 3 <i>Supervised Driving</i>	2.60	0.14	65	2.63	0.13	59	2.65	0.16	49
				<i>Supervised Driving</i>			<i>Supervised Driving</i>		
Type 4 <i>Self-Driving Test Vehicle</i>	2.52	0.15	65	2.53	0.11	59	2.45	0.13	51
				<i>Self-Driving Test Vehicle</i>			<i>Self-Driving Test Vehicle</i>		
Type 5 <i>Intermittent Self-Driving</i>	1.59	0.18	63	1.62	0.17	58	1.35	0.18	49
				<i>Conditional Self-Driving</i>			<i>Part-Time Self-Driving</i>		
Type 6 <i>Driverless</i>	3.06	0.14	64	2.90	0.14	58	2.43	0.20	51
				<i>Full-Time Self-Driving</i>			<i>Autonomous Driving</i>		

Following the selection procedure described above, the proposed terms with the highest mean accuracy scores were compared with the average of the scores from the SAE levels. Figure 4 shows the resulting accuracy scores by automation type.

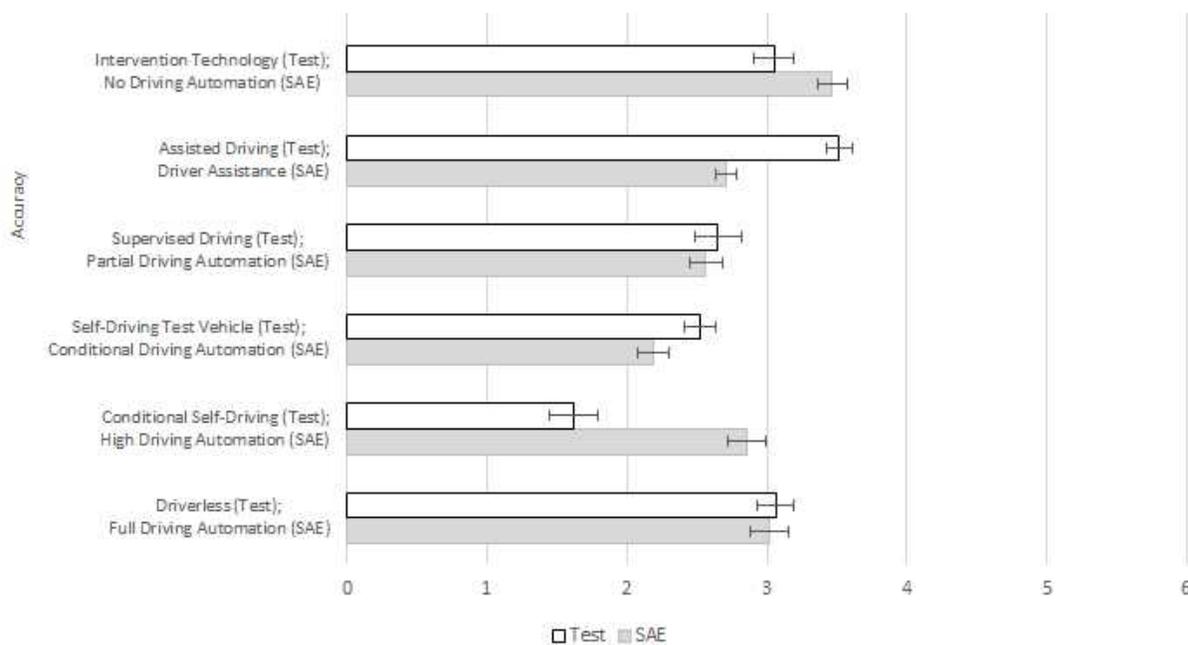


Figure 4. Comparison of highest scoring proposed and SAE automation types accuracy scores.

For Type 1, the mean accuracy score for “Intervention Technology” (proposed) was significantly lower than for “No Driving Automation” (SAE Level 0), $t(170)=2.62$, $p = .01$. For Type 2, “Assisted Driving” (proposed) was significantly higher than “Driver Assistance” (SAE Level 1); $t(163)=6.55$, $p < .01$. For Type 3, “Supervised Driving” (proposed) was non-significantly different than “Partial Driving Automation” (SAE Level 2), $t(153)=0.98$, $p = .33$. For Type 4, “Self-Driving Test Vehicle” (proposed) was significantly higher than “Conditional Driving Automation” (SAE Level 3), $t(168)=2.17$, $p = .03$. For Type 5, “Conditional Self-Driving” (proposed) was significantly lower than “High Driving Automation” (SAE Level 4), $t(163)=5.74$, $p < .001$. For Type 6, “Driverless” (proposed) was non-significantly different than “Full Driving Automation” (SAE Level 5), $t(169)=0.82$, $p = .41$.

Perceived Fit

The same set of proposed terms that ranked highest on accuracy were used for comparison with SAE automation types on perceived fit. Figure 5 shows the perceived fit scores by automation type.

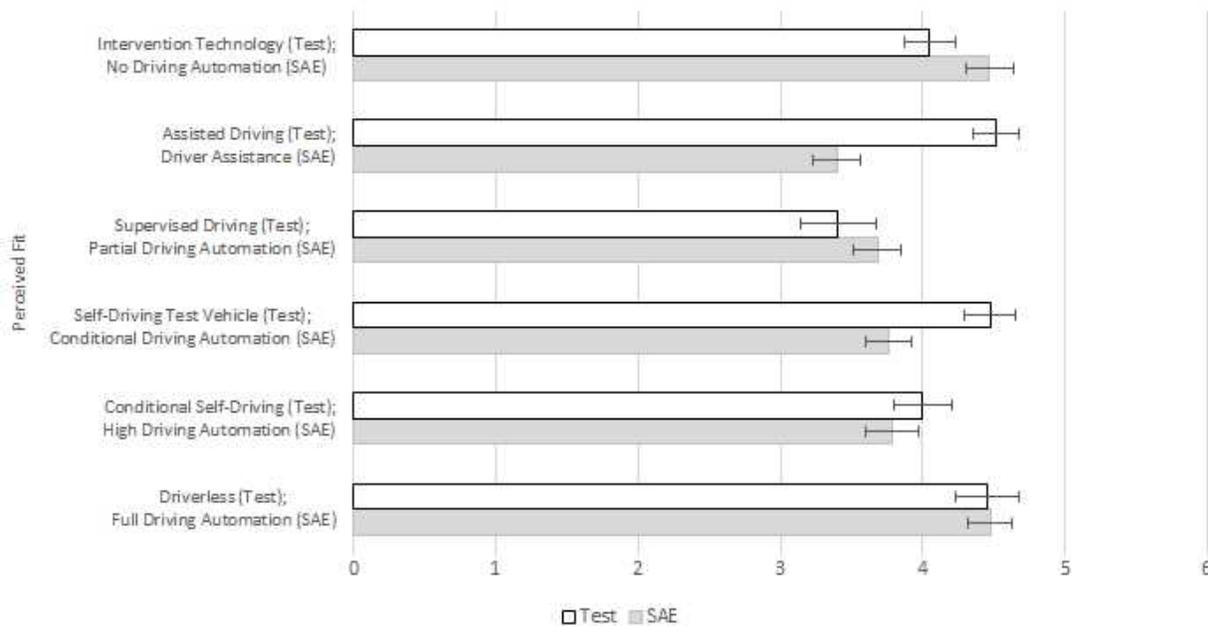


Figure 5. Comparison of proposed and SAE automation types perceived fit scores.

For Type 1, the mean fit score for “Intervention Technology” (proposed) was marginally lower than for “No Driving Automation” (SAE Level 0), $t(170)=1.91, p = .06$. For Type 2, “Assisted Driving” (proposed) was significantly higher than “Driver Assistance” (SAE Level 1); $t(163)=4.56, p < .01$. For Type 3, “Supervised Driving” (proposed) was non-significantly different than “Partial Driving Automation” (SAE Level 2), $t(153)=1.34, p = .18$. For Type 4, “Self-Driving Test Vehicle” (proposed) was significantly higher than “Conditional Driving Automation” (SAE Level 3), $t(161)=3.05, p < .01$. For Type 5, “Conditional Self-Driving” (proposed) was non-significantly different than “High Driving Automation” (SAE Level 4), $t(163)=1.21, p = .23$. For Type 6, “Driverless” (proposed) was non-significantly different than “Full Driving Automation” (SAE Level 5), $t(166)=0.73, p = .47$.

Discussion

In comparing accuracy and perceived fit between the proposed terms and the SAE terms (and their associated definitions), the results showed a mixed benefit of the proposed set over the SAE set. The proposed terms and definitions were intended to provide a clear set of descriptors for driver responsibilities. However, varying the terms (Sets 1, 2, & 3) for the proposed set of definitions produced only marginal benefits of increased driver accuracy in understanding those responsibilities. As compared to the SAE terms and definitions, the highest scoring proposed terms produced two significantly higher accuracy scores out of the total set of six. Across term types, the highest accuracy scores (above 3) were at the ends of the automation scale “Assisted Driving” and “Driverless” as well as “No Driving Automation”. These results were mirrored with perceived fit, with the exception of “Self-Driving Test Vehicle”, which also ranked high (above 4) among the total set of terms.

Conclusion

This survey exercise revealed that a sample of vehicle consumers had a low to moderate (2.77) understanding of six different automation types. Across six types, participants were most accurate in distinguishing either ends of a LoA scale.

From the survey exercise summarized in the previous section, one takeaway conclusion was that a 6-level taxonomy produces a greater degree of confusion in role responsibility than the end points, regardless of terminology. For both term types and definitions (proposed & SAE), consumers were best able to differentiate the extremes of automation types, leading to the question of whether or not it may be beneficial to provide a simplified representation to communicate functionality.

At core and in simplest form, a driver needs to understand when s/he is responsible for driving (e.g. lateral and longitudinal control, OEDR, etc.) and when, instead, the types of automation on-board the vehicle are responsible for vehicle control. The details beyond this binary classification are in need of further study and, most importantly, may not be needed to successfully communicate to drivers key differences in car technologies. As an initial representation, a set of car technology types are listed in Figure 6 according to the duration of time they conceptually provide their intended benefit(s) (i.e. red boxes within the two dashed black boxes). Figure 6 extends the “driving” vs. “riding” framing of automation, placing car technology types in terms of a consumer-oriented expected benefit in getting from “Point A” to “Point B”.

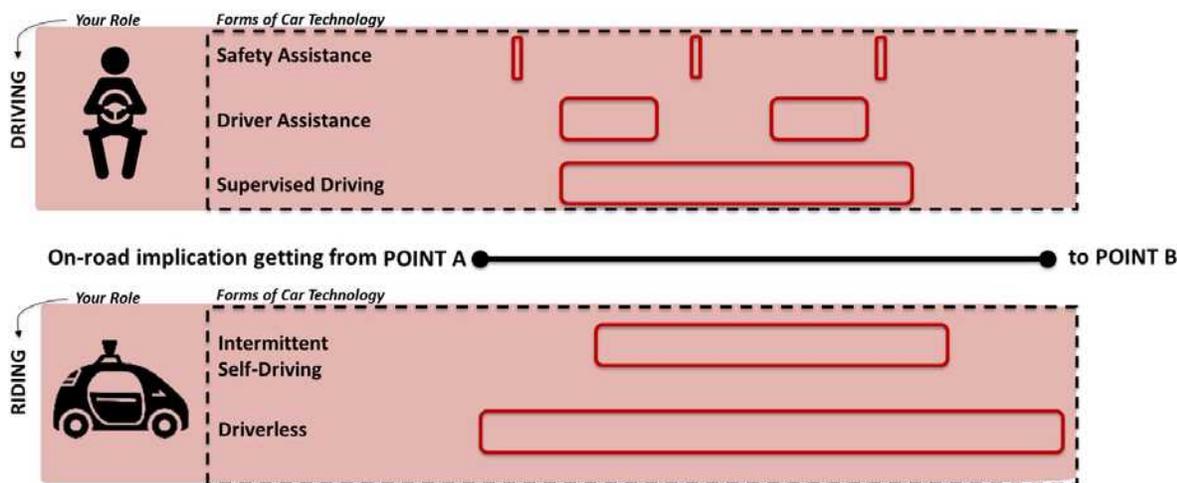


Figure 6. Two key consumer takeaways important to communicate in a taxonomy: Primary role responsibility (driver or vehicle) and duration of engagement (i.e., functional benefit to consumer).

Average drivers may someday possess a greater degree of experience and understanding necessary to accurately consider the parsing of functionality for more complex engineering

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definitions of automated systems. Until it becomes a necessity to fully conceptualize automated driving systems in this way, however, a more simplistic communication mechanism using a binary framing such as “driving” and “riding” may be best suited to ensure consumer understanding. Educational efforts need to be invested in drivers’ understanding of and ability to use various forms of vehicle automation. With either the new simplified dichotomy or the continued use of the 6-level SAE taxonomy, driver education around our new and evolving role as a partner with automation is a core area of need and future research.

Acknowledgments

Support for this work was provided by the New England University Transportation Center at MIT and the Advanced Vehicle Technology (AVT) consortium at MIT. The views and conclusions being expressed as those of the authors and may not necessarily represent those of individual sponsoring organizations.

References

- Abraham, H., Seppelt, B., Mehler, B., & Reimer, B. (2017). What's in a name: Vehicle technology branding & consumer expectations for automation. In *Proceedings of the 9th International ACM Conference on Automation User Interfaces and Interactive Vehicular Applications*, September 2017.
- Bailey, N., & Scerbo, M. (2008). Automation induced complacency for monitoring highly reliable systems: the role of task complexity, system experience, and operator trust. *Theoretical Issues in Ergonomics Science*, 8(4), 321-348.
- Bainbridge, L. (1983). Ironies of automation. *Automatica*, 19(6), 775-779.
- Bhana, H. (2010). Trust but verify. *AeroSafetyWorld*, June 2010.
- Bradshaw, J.M., Hoffman, R.R., Johnson, M., & Woods, D.D. (2013). The seven deadly myths of “autonomous systems”. *Human-Centered Computing, IEEE Intelligent Systems*.
- Campbell, J. L., Brown, J. L., Graving, J. S., Richard, C. M., Lichty, M. G., Bacon, L. P., ... & Sanquist, T. (2018, August). *Human factors design guidance for level 2 and level 3 automated driving concepts (Report No. DOT HS 812 555)*. Washington, DC: National Highway Traffic Safety Administration.
- Casner, S. M., Geven, R. W., Recker, M. P., & Schooler, J. W. (2014). The retention of manual flying skills in the automated cockpit. *Human Factors*, 56(8), 1506-1516.
- Cook, R.I., Woods, D.D., McColligan, E., Howie, M.B. (1990). *Cognitive consequences of 'clumsy' automation on high workload, high consequence human performance, SOAR 90, Space Oper. Appl. Res. Symp.* (NASA Johnson Space Center 1990).
- Flemisch, F., Winner, H., Bruder, R., & Bengler, K. (2014). Cooperative guidance, control and automation. *Handbook of Driver Assistance Systems: Basic Information, Components and Systems for Active Safety and Comfort*, 1-9.
- Lee, J. D. (2018). Perspectives on Automotive Automation and Autonomy. *Journal of Cognitive Engineering and Decision Making*, 12(1), 53-57.
- Lee, C., Seppelt, B., Mehler, B., & Reimer, B., & Coughlin, J. (2018). Consumer Comfort with In-Vehicle Automation: Technology of Today Drives Acceptance of a Self-Driving Future. *White Paper 2018-2 – MIT AgeLab*, September 2018.
- Merat, N., Seppelt, B., Louw, T., Engström, J., Lee, J. D., Johansson, E., ... & McGehee, D. (2018). The “out-of-the-loop” concept in automated driving: Proposed definition, measures and implications. *Cognition, Technology & Work*, 1-12.
- Onnasch, L., Wickens, C. D., Li, H., & Manzey, D. (2014). Human performance consequences of stages and levels of automation: An integrated meta-analysis. *Human factors*, 56(3), 476-488.
- Prinzel, L., DeVries, H., Freeman, F., & Milulka, P. (2001). *Examination of automation induced complacency and individual difference variates*. Hampton, Virginia, U.S.: National Aeronautics and Space Administration Langley Research Center.

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SAE, Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles, *SAE Standard J3016*, USA, 2018.

Seppelt, B.D., & Lee, J.D. (Submitted). Keeping the driver in the loop: Enhanced feedback to support appropriate use of imperfect vehicle control automation. *International Journal of Human-Computer Studies*.

Seppelt, B.D., Reimer, B., Angell L., & Seaman, S. (2017). Considering the human across levels of automation: Implications for reliance. *Driving Assessment Conference: 9th International Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design*, June 2017.

Seppelt, B. D., & Victor, T. W. (2016). Potential solutions to human factors challenges in road vehicle automation. In *Road Vehicle Automation 3* (pp. 131-148). Springer.

Victor, T. W., Tivesten, E., Gustavsson, P., Johansson, J., Sangberg, F., & Ljung Aust, M. (2018). Automation expectation mismatch: incorrect prediction despite eyes on threat and hands on wheel. *Human factors*, 60(8), 1095-1116.

Wickens, C. D., & Kessel, C. (1981). Failure detection in dynamic systems. In *Human detection and diagnosis of system failures* (pp. 155-169). Springer, Boston, MA.

Wickens, C. D., Li, H., Santamaria, A., Sebok, A., & Sarter, N. B. (2010, September). Stages and levels of automation: An integrated meta-analysis. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 54, No. 4, pp. 389-393). Sage CA: Los Angeles, CA: Sage Publications.

Woods, D. D. (2016). The risks of autonomy: Doyle's catch. *Journal of Cognitive Engineering and Decision Making*, 10(2), 131-133.

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The Massachusetts Institute of Technology AgeLab conducts research in human behavior and technology to develop new ideas to improve the quality of life of older people. Based within MIT's Center for Transportation & Logistics, the AgeLab has assembled a multidisciplinary team of researchers, as well as government and industry partners, to develop innovations that will invent how we will live, work and play tomorrow. For more information about AgeLab, visit agelab.mit.edu.

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