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RESEARCH ARTICLE

Identifying Factors That Impact Levels of Automation in Autonomous Systems

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ABSTRACT The need to support complex human and machine collaboration has increased because of recent advances in the use of software and artificial intelligence approaches across various application domains. Building applications with more autonomy has grown dramatically as modern system development capability has significantly improved. However, understanding how to assign duties between humans and machines still needs improvement, and there is a need for better approaches to apportion these tasks. Current methods do not make adaptive automation easy, as task assignments during system operation need to take knowledge about the optimal level of automation (LOA) into account during the collaboration. There is currently a lack of explicit knowledge regarding the factors that influence the variability of human-system interaction and the correct LOA. Additionally, models have not been provided to represent the adaptive LOA variation based on these parameters and their interactions and interdependencies. The study, presented in this paper, based on an extensive literature review, identifies and classifies the factors that affect the degree of automation in autonomous systems. It also proposes a model based on feature diagrams representing the factors and their relationships with LOAs. With the support of two illustrative examples, we demonstrate how to apply these factors and how they relate to one another. This work advances research in the design of autonomous systems by offering an adaptive automation approach that can suggest levels of automation to facilitate human-computer interactions.

INDEX TERMS Software engineering, levels of automation, adaptive system, autonomous systems, software design.

I. INTRODUCTION

Quality, productivity, accuracy, precision, and other metrics are usually improved when machines perform tasks previously assigned to humans [1]. What is the best choice to execute a specific task, a human or a machine? Many debate the advantages and disadvantages of fully automating tasks as opposed to keeping humans involved [2]. However, rather than automation being an all-or-nothing proposition, many levels of automation can be used, ranging from entirely manual to fully autonomous [1], [3].

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So-called autonomous systems such as self-driving automobiles or trucks, autopilots on airplanes, robots, machine tools, chatbots and 'smart' buildings still need human intervention under various conditions such as sudden changes in traffic, weather conditions, environment, or materials. Thus, these so-called autonomous systems need to operate independently to achieve the highest degree of automation possible while they need to be designed to accept human intervention when necessary or appropriate. Although autonomous systems use machine learning, which recognizes long-term patterns, sometime such systems must recognize short-term situations, a task at which humans are particularly competent.

What are the principles that should be used to design such systems, and can we develop a software engineering discipline that addresses autonomous system design? In this paper, we identify factors that are common to autonomous systems and should be considered when developing a software design approach.

Few methods or resources are available to support the flexible and scalable assignment of tasks between humans and machines within autonomous systems [4], [5]. The relationship and responsibility for distributing tasks between humans and machines within autonomous systems are not clearly defined, and the level of automation is far from uniform across various contexts. Thus, modelling techniques that can systematically support task distribution across a wide range of automation levels are needed.

There are inherent challenges in developing and researching the automation variability levels of these systems. When developing autonomous systems, the computational complexity and memory footprint of algorithms play a crucial role in the design and implementation of such, as these systems must be developed with computation times that satisfy real-time responses [6],

Moreover, these systems differ by quality standards, such as in the application or the agent responsible for automating the task. These applications can also change if the perspective or feedback of the person interacting with the agent differs and depends on human resources and the system's ability. To design systems properly that support different levels of automation, developers must be provided with a clear understanding of the relevant factors that influence levels of automation and with design criteria for addressing them [7].

We address this gap by identifying, refining, and representing the factors that can influence a level of automation decision. We also introduce an approach to capture the factors that influence levels of automation in autonomous systems. The approach presents several changes inherent in developing these autonomous systems, including those related to systems and humans. This approach aims at answering the following research question: **RQ: Which factors affect the variance of levels of automation in autonomous systems?**

As specific contributions, this paper:

- Presents an approach to identify the factors that influence levels of automation
- Provides a list and categorization of the factors that influence levels of automation
- Refines the identified factors by demonstrating how systems can capture these factors
- Introduces a representation of the variability of the factors and their relationships with LOAs in a feature diagram
- Demonstrates the feature diagram and approach with illustrative examples

We structure this paper as follows: Section II presents the related work. We provide details about our methodology in Section III. Sections IV and V describe the approach for identifying the factors influencing LOA, their relationships with LOAs, a resulting table of the categorized factors and a refinement of the identified factors. Section VI presents the representation of the variability of the identified factors. To illustrate and clarify the proposed approach with examples, we present examples of the instantiated feature model in different scenarios in Section VII. We discuss our findings in Section VIII and conclude the paper with our final remarks and future work in Section IX.

II. RELATED WORK

Research into building systems that adapt while interacting with humans has a long history. In the '70s, Sheridan and Verplank [8] introduced a study on what they call "supervisory control". The authors explain that there is supervisory control if a system has sensors, actuators and a computer capable of making autonomous decisions and being operated by a person. They concentrate on the prospects of using supervisory control in a specific domain (navy undersea tasks), providing substantial contributions through experimental observation. According to the authors, automation includes "the mechanization and integration of the sensing of environmental variables; data processing and decision making; mechanical action; and "information action" by communicating processed information to people." Their work also proposes a taxonomy for levels of automation in machine-computer collaboration.

More recently, the work of Parasuraman and Sheridan [9] builds upon Sheridan and Verplank's work. The authors propose a level of automation taxonomy that ranges from 1 (the computer offers no assistance, and the human must take all decisions and actions) to 10 (the computer decides everything and acts autonomously, ignoring the human). The authors argue that automation can be applied at several stages, including (1) information acquisition, (2) information analysis, (3) decision and action selection, and (4) action implementation, and levels of automation can be employed in each of these stages. They propose a model with human performance as the central criterion for using their proposed model.

Research has focused on allocating tasks between humans and machines, assisting adaptive automation system design. Bindewald et al. [10] propose a process model that can be used by design to investigate how tasks are distributed when users engage with adaptive systems. According to the authors, information flows change as tasks are transferred or assigned to either humans or machines. They look at five analysis methods that show where human-machine transitions are required.

The review of related works in this field shows that there has been significant progress in understanding the interaction between humans and autonomous systems. Specifically, previous work has focused on developing taxonomies and models that describe the levels of automation in systems and the allocation of tasks between humans and machines. However, there is still a need for a more comprehensive understanding of the factors that influence the switch between levels of automation and how they interact.

This paper contributes to the field by analyzing a wide range of existing literature and identifying the factors that influence the levels of automation in autonomous systems. In addition, this paper presents a new model that categorizes these factors and represents them in a systematic and organized way. Designers and researchers can use this model to understand better the factors that impact the levels of automation and how to design systems that effectively adapt to changing circumstances. Overall, this paper provides a valuable contribution to the field of autonomous systems and human-machine interaction by providing a more comprehensive understanding of the factors that influence the levels of automation in such systems. By building upon and extending the existing research, this paper offers a valuable resource for researchers and designers working in this field, helping to develop more effective autonomous systems that can better adapt to changing circumstances and interact more effectively with human users.

Next, we detail the studies related to these main topics, namely automation in autonomous systems, levels of automation, and task distribution between humans and machines. We include a deeper discussion on each topic, identifying research in these three main areas.

A. AUTOMATION IN AUTONOMOUS SYSTEMS

In the past few years, the development of autonomous systems has increased, with an increasing focus on integrating automation within these systems. For example, in uncrewed aerial vehicles (UAVs), researchers have explored various methods to automate the control of these vehicles [11]. These methods include using deep learning to detect and avoid obstacles for uncrewed vehicles [12], using reinforcement learning to optimize autonomous driving agents [13] and developing specific software stacks to support the advance of self-driving cars [14]. Moreover, researchers have also investigated how variations influence trust in an autonomous system in system speed, accuracy, and uncertainty. This study demonstrated that humans are likelier to miss system errors when highly trusting the system. The level of self-correction with which an automated system produces responses can also impact human trust [15].

B. LEVELS OF AUTOMATION

Levels of automation (LOA) have been widely used to describe the degree to which a system is automated, ranging from fully manual to fully autonomous. Several taxonomies have been proposed to categorize different levels of automation, such as the Parasuraman and Sheridan taxonomy mentioned earlier. In recent years, researchers have extended these taxonomies to specific domains. The work of Machado et al. [16] focuses on the heavy-duty mobile machinery industry and presents a two-dimensional 6×6 matrix. While the work of Kugele et al. [17] presents a four-level taxonomy that provides a foundation for describing future systems, including robotic and drone taxi systems.

C. TASK DISTRIBUTION BETWEEN HUMANS AND MACHINES

Research into task allocation between humans and machines has been ongoing for decades, with many studies focusing on the distribution of tasks and how to achieve optimal performance through effective collaboration. Bindewald et al. [10] proposed a process model that can be used to investigate how tasks are distributed when users engage with adaptive systems. The authors looked at five analysis methods that show where human-machine transitions are required, and their proposed model can assist in the design of adaptive automation systems.

More recently, Buerkle et al. [18] discussed the challenges of human-robot collaboration in manufacturing. The authors propose an adaptive human sensor framework that incorporates objective, subjective, and physiological metrics to address the challenge of equipping the robot with a model of the human. The framework was tested to predict perceived workload during manual and human-robot collaboration assembly tasks. The results showed promising potential for the framework to enable a more effective human-robot collaboration by adapting to human behaviour's uniqueness and dynamic nature.

In another study, Bejarano et al. [19] investigated the significant increase in the use of robots in factories to improve productivity and efficiency and the fact some manual tasks requiring dexterity still cannot be performed by robots alone. To address this, collaborative robots, also known as "cobots," have been developed to allow for safe interaction between robots and human operators. These authors present a case study of a human-robot collaborative assembly workstation that uses a robot to assemble a product box. The benefits and challenges of implementing cobots are discussed, and the study shows that collaborative interaction between cobots and human operators is feasible and advantageous for industrial facilities.

Furthermore, the recent work of Wang et al. [20] on automated scoring of subjective assignments (ASSA) reveals there can be a large difference between the scores given by the machine and those given by human evaluators when grading high or low-quality essays. The authors' study proposes a collaborative human-machine approach to scoring essays, combining human judgement and machine learning algorithms. They propose a framework which allocates tasks between humans and machines based on three-way decisions. Their experiments show that the proposed framework achieves higher execution efficiency than seven other baseline models and improves the accuracy of essay grading by 19.31% while using only 19.02% of the human workload.

III. RESEARCH METHODOLOGY

We conducted a systematic literature review (SLR) to answer the research question posed in the Introduction. In this section, we describe the methodology used to select the papers from where we should extract the factors that influence levels

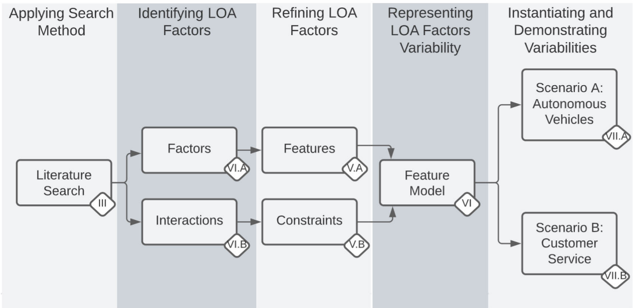

FIGURE 1. **Overview of the approach.**

of automation. To answer the proposed research question and investigate which factors impact the LOA variability in systems that support human-machine interactions, we have followed the approach illustrated in Figure 1. This figure shows how we present and organize the contributions and results of our work and relates the content to the paper structure by showing the reference index number of the paper sections inside the diamond shapes.

This study aims to identify the factors that influence levels of automation. Moreover, we represent the variability of the factors and their relationships with LOAs in a feature model [21], [22] and illustrate these variabilities with examples in different domains. The advantages of identifying the factors that govern human and autonomous systems interactions are manifold. Intelligent automation is one of the current emerging technologies. The ultimate purpose is to build autonomous systems that can handle edge cases and achieve the highest degree of automation possible. Building systems that consider human interaction and how this interaction impacts the system's behaviour leads to better system designs in terms of accuracy. As humans are better at spotting patterns in small data sets, combining human and artificial intelligence can provide highly accurate systems. Rule-based automation can sometimes be more precise than AI-based intelligent automation, while AI models are only partially correct. After all, no matter how perfectly you design a fully automated system with all possible outcomes, the reality is frequently complicated. Human-free end-to-end process automation is attractive because it is significantly easier to implement than systems that require human input. Our work mitigates these issues and difficulties by bringing to light factors, a model and illustrative examples to support the design and implementation of autonomous systems interacting with humans. The approach to supporting the design of autonomous systems is described next.

To identify the relevant studies, we searched several databases using keywords related to levels of automation and factors influencing automation. We also manually searched the reference lists of relevant articles to identify additional studies. Our inclusion criteria were studies investigating factors influencing automation levels in systems supporting human-machine interactions. We excluded studies that did not meet our inclusion criteria, were not written in English, or were published before 2000 (including only papers published within the last 23 years). Two researchers participated in the selection of the included articles.

A. APPLYING SEARCH METHOD

We started the research by examining secondary studies summarizing taxonomies for levels or degrees of automation in autonomous systems published since 2000 [1], [23]. (Figure 1, Literature Search, Section III). Secondary studies synthesize or analyze published research. Secondary studies can help researchers identify the most relevant and high-quality primary studies on a particular topic. They can also help them identify gaps or inconsistencies in the existing literature [24]. These studies are recent, and they follow systematic review protocols and report extensive results. Together they provide an important baseline for the topic. From these secondary studies, we performed backward and forward snowballing (one level in each secondary study paper). This step aims to identify proposed levels of automation and the factors (contexts, characteristics) that influence the levels of automation in these studies.

As exclusion criteria [24], we excluded papers not written in English and those that do not have information on factors that affect automation levels. All other articles were considered.

B. IDENTIFYING LOA FACTORS

For each LOA factor identified, we kept a record of the information in a spreadsheet. If the same information was found in another paper, we recorded the citation with the already listed factor. Each citation provides a scientific basis for the factors we identified. We then categorize each factor into more abstract concepts. For example, if the factors were Role and Cognitive Ability, these factors would be abstracted into "Human" factors. If the factors were maintainability and reliability, these factors would be categorized into "Quality" (Non-Functional Requirements) factors.

Two researchers reviewed over 150 papers and extracted and categorized the factors together. We used the inter-rater reliability measure with Cohen's kappa statistical coefficient to measure the degree of agreement between the two researchers (judges) categorizing the identified factors [25]. The two researchers almost always agreed when categorizing the factors (k between 0.81 $\times$ 1.00). This research methodology aims to contribute to the state-of-the-art by illustrating the factors impacting automation levels and representing these factors and their relationships with LOAs (Figure 1, Section IV). The ultimate goal of our work is to support the design and implementation of autonomous systems interacting with humans. To achieve this, we will provide models, refinements, use cases and discussions on our findings. By highlighting the factors influencing LOAs and their variabilities, we aim to improve the effectiveness and usefulness of autonomous systems and ultimately facilitate their widespread adoption.

C. REFINING LOA FACTORS

Next, we organize these factors and categorize them into a table (Section IV and subsections) and provide examples of how these factors may be implemented in systems. (Figure 1, Section V).

D. REPRESENTING LOA FACTOR VARIABILITY

We then represent the factors and the relationship between the identified factors and LOAs using a feature diagram (Figure 1, Section VI).

E. INSTANTIATING AND DEMONSTRATING VARIABILITIES

Last, we present examples of the application of the features and constraints (Figure 1, Section VII). Three authors met after the last iteration to review the feature model, our final contribution to this paper.

The following section presents the identified LOA factors based on the approach just described.

IV. IDENTIFYING LOA FACTORS

In this section, answering the **RQ** proposed in this study, we present the factors that influence levels of automation. We categorize these factors and present each of the categories in a subsection. The result of our analysis and categorization is presented in Table 1. This table illustrates the factors that influence the autonomy level decision. This table has four columns related to the factors identified in the literature review and one column related to the authors that cite each factor in the literature. Working across the table, each factor, if applicable, is further divided into subfactors. In other words, the factor information in the column to the right is related to the last row of the cell on the left. Then, we describe the classification of the factors, provide examples, and discuss how factors can influence LOAs.

A. IDENTIFYING FACTORS

Based on the literature review and after categorizing the factors, the result is five main factors that can influence the decision to adopt specific LOA: Quality, Agent (System), Human, Task and Environment. These factors are assembled and categorized in Table 1, and their descriptions are provided next.

1) QUALITY

Sheridan and Verplank [8], Khuat et al. [26], Proud et al. [27], and Beer et al. [28] identified quality criteria in systems that support some sort of autonomy. These authors describe factors such as Trust, Reliability, Fairness, Transparency and Accessibility. For instance, a system should provide a higher LOA in the tasks that this system is expected to carry out if this system is reliable (success in testing). These authors also mention Explainability, Understandability, Maintainability, Usability, Safety, Ethics, Legal compliance, and System Adaptability of the system as factors that influence levels of automation.

2) TASK

There are factors specifically related to the task's characteristics that influence a system's LOA. For example, the result of the task (failure/success) and quality factors specific to the task, such as Performance, Complexity, Risk and Accessibility [7], [8], [29], [30], [31]. Other factors related to the task, such as Workload [5], [32], Frequency of a task [7] and Interaction Type [4] also influence LOAs.

3) AGENT

One central factor affecting automation levels in autonomous systems is the Communication [8], [31], [35] between the human and the system. In the context of teams, a human (team member) can interact with the automated system as a team member or in the form of supervisory control [35]. Another identified factor is the cost of this system, namely the equipment's operating cost and the implementation cost of the agent [27], [34]. Other factors we have identified are related to the capabilities of this system, including Reactiveness, Situation Awareness, Decision Capability and Feedback capabilities [4], [7], [31], [36], [37], [38]. Other capabilities of the agent influence the desired level of automation. For example, the Transparency of the agent regarding its procedures and goals [23], [28], or how the agent acquires and analyzes information [9]. Ability is explicitly also mentioned as one factor, as well as the Authority of the agent executing work autonomously [2].

4) HUMAN

Many factors related to the person interacting with the system can influence the decision of LOAs. Authors refer to the age of the person interacting with a system [32], the recognition of the time to acquire control or the time to give up the control [39], the person's cognitive ability [32], [39] and other factors. Many authors point to factors related to how humans interacting with the system perceive the system [28], [30], the task the system is supposed to execute [29], [36], [44] and the humans themselves [32], [36], [44].

5) ENVIRONMENT

Our research shows that the environment can also impact a system's LOA. Authors discuss this variability in terms of the environment as either dynamic or static [23], [45]. Khuat et al. [26] also describe factors such as the Competing tasks or Demands of the environment as aspects that influence the LOA of systems.

We have answered the Research Question proposed in this study by identifying in the literature the factors that impact the level of automation of systems that interact with humans. Next, we explain how these factors can influence levels of automation.

B. IDENTIFYING HOW FACTORS IMPACT LOAs

To demonstrate the relationship between the identified factors and a level of automation, we have also extracted from the same papers in the SLR how a combination of factors can

TABLE 1. Levels of automation factors and authors citing each factor.

Factors				Authors
Quality				
	Trust			[27] [28]
	Reliability			[8] [26]
	Fairness			[26]
	Transparency			[26]
	Accessibility			[26]
	Explainability			[26]
	Understandability			[26]
	Maintainability			[26]
	Usability			[26]
	Safety			[26]
	Ethic			[26]
	Law Compliance			[26]
	Adaptability			[26]
Task				
	Result			[23] [33] [5]
	Quality			[23] [33] [5]
		Performance		[7] [29]
		Complexity		[8] [30] [31]
		Risk		[30]
	Workload			[32] [5]
	Frequency			[7]
	Interaction Type			[4]
Agent				
	Cost			[34] [27]
	Communication (verbal)			[8] [35] [31]
	Capability			
		Reactive		[31] [36] [37]
		Situation Awareness		[7] [38] [37]
		Decision Capability		[38] [4] [37] [9]
		Feedback		[8]
		Recovery Ability		[39] [36] [37]
		Team Cooperation (push/pull)		[35]
		Context (domain)		[36] [4] [5]
		Adaptability		[23] [37] [28]
		Systematic process		[37]
		Safety		[33]
		Transparency		[23] [28]
		Intelligence		[28]
		Information Acquisition and Analysis		[9]
		Action implementation		[9]
		Architecture		[40]
		Ability		[2]
		Authority		[2]
Human				
	Age			[32]
	Control timing			[39]
	Cognitive Ability			[39] [32] [40]
	Situation Awareness			[29] [41] [31] [42] [36] [28] [43] [26]
	Performance			[35] [32] [43]
	Role			[41]
	Workload			[8] [7] [30] [28] [43]
	System Acceptance			[7] [28]
	Knowledge			[32] [40]
	Skill			[30] [40] [36] [32]
	Attention Demand			[4] [26]
	Engagement			[36]
	Social Skills			[28]
	Perception			
		System		
			Reliability (trust)	[30] [28] [26]
		Task		
			Workload (heavy/light)	[29] [44] [36]
		Self		
			Tension (tense/calm)	[44] [36] [32]
			Fatigue (tired/rested)	[44] [36] [32]
			Confidence (high/low)	[44] [36] [32]
Environment				[23]
	Variability			[45] [32] [23]
		Unchanging/Highly Dynamic		[45]
	Competing tasks			[26]
	Demands			[26]

influence a level of automation. It should be highlighted that the factors and their relationships with LOAs are intended to be "reasonable" hypotheses to examine the possibilities for a formal treatment of qualitative factors.

Riley et al. [30] give strong examples of the relationship between one or many factors and levels of automation. They claim that if there is an error with the system, humans are less likely to trust the system, and the LOA tends to have high levels of human control. As humans trust the system (high reliability, high trust), LOAs can be more autonomous. According to their hypothesis, these authors then claim that "trust takes longer to be rebuilt than to be destroyed" and that humans tend not to change their opinion even as their experience with the system increases.

High system reliability –> more automation. Low system trust –> more manual work.

Proud et al. [27] discuss the autonomous system/agent cost. They claim that increased autonomy levels throughout the design phase are expensive (high cost) and time-consuming. However, if properly implemented, they raise operational safety and effectiveness, which could lower total system lifespan costs. It is essential for designers of autonomous systems to then weigh the advantages of effectiveness and operational safety of autonomous systems over their cost.

High cost to design system –> more automation –> cost mitigated over system lifespan.

Factors such as trust and costs (or design tradeoffs) are still abstract. To systemize levels of automation, factors such as reliability, perceived risk, and many others should become more concrete so that system specifications can capture them. Next, we provide a refined view of the factors we have identified. We present the factors as features a system can capture and describe how these features can influence levels of automation once captured.

C. METHODOLOGY HIGHLIGHTS AND CHALLENGES

Assessing the research methodology proposed in our work, we list our method's highlights (strengths) and challenges (weaknesses) below.

Strengths:

- The methodology is clearly outlined and easy to follow, making it easier for other researchers and the software engineering community to replicate or build upon the study
- The research question and objectives are explicitly stated, which helps to maintain focus throughout the study
- A systematic literature review (SLR) conducted by two authors, providing a rigorous and comprehensive approach to selecting relevant papers and extracting data from them
- The researchers used online collaboration tools to control their versions of files and control file edits, enhancing the findings' reliability and validity
- The use of inter-rater reliability measures to ensure consistency in categorizing the identified factors adds to the robustness of the study
- The researchers clearly state the significance of their work and how it contributes to the field, which helps to justify the research and its outcomes

Weaknesses:

- The study only includes papers published in English and after 2000, which may limit the generalizability of the findings. However, we do include a comprehensive review of the related works and background
- The exclusion of non-English papers and those published before 2000 may have resulted in the omission of relevant studies or factors influencing levels of automation
- The use of backward and forward snowballing may have also limited the review's scope and missed important papers or factors that were not cited in the selected articles
- The methodology does not clearly justify categorizing the identified factors into more abstract concepts, which may lead to potential biases or subjectivity in the analysis. We mitigated this by having two researchers categorize the factors and using Cohen's kappa statistical measure.

V. REFINING LOA FACTORS

Many of the factors identified in the literature are abstract. In other words, capturing these factors through a system or a feature is not straightforward. For example, the factor of "reliability." How can we capture the reliability of a system? However, our goal is to allow an autonomous system capable of identifying these factors to assign a level of automation to that task. Therefore, this section shows how to relate abstract factors to concrete ones. In other words, factors that can be captured by a system or features that can be used to build systems. We will refine the meaning of these factors as stated by the authors and illustrate the factors with examples. We extract one factor from each category to show how to transform an abstract factor into a concrete one that can be used in a system capture. We are calling these concrete factors the "Features" and the interaction between the features we call "Constraints." Features and constraints are described next.

A. CAPTURING FACTORS AS FEATURES

This research program extracts factors that influence LOAs. To apply these factors systematically, we discuss in this section how to convert these factors into features or concrete factors. The features, their meaning, quotes from the papers where those features were extracted, and an example of the use of the feature are demonstrated in detail in the following sections. We present one or more features from each factor category (Quality, Task, Agent, Human and Environment).

1) QUALITY

Transparency [26]. Meaning: the system can show the reasoning behind its results. Quote from paper [26]: "The reluctance by people to use results they cannot understand or explain can be frustrating for simple business applications, but it is completely warranted in high-stakes contexts, including medical diagnosis, financial investment and criminal justice. To do otherwise could be disastrous."

Explanation: Can the system show the reasoning behind its code/algorithms? If yes: the system is transparent. If not: the system is not transparent.

2) TASK

Frequency [7]. Meaning: how many times a task is executed. Quote from the paper [7]: "In addition to reducing workload, expert systems can further augment the user by providing new capabilities never possessed before. Bearing this in mind and armed with an understanding of the user's needs, the actual selection of expert system applications can proceed with additional inputs in task frequency, task criticality, technological capabilities and user acceptance."

Explanation: depending on how often one task is executed (frequency), this task can be a suitable candidate for full or more automation.

3) AGENT

Adaptability [23]. Meaning: Capacity of the system to adapt and improve its performance in a particular environment without human intervention. Quote from the paper [23]: "Adaptability is usually considered crucial for technical autonomy. Being autonomous requires learning and adapting behavior to a changing environment. A machine of this kind can process information, expanding the knowledge implemented by programmers and changing how the system responds. This allows the system to adapt and improve its performance within an environment without human intervention. Thus, adaptable systems can alter their behavior, making them more unpredictable and independent of human operators. Adaptability, therefore, shapes technical autonomy."

Explanation: Is the system adaptable? If yes, provide more autonomy. If not, allow for manual/human intervention.

4) HUMAN

Workload [7], [8], [28], [30], [43]. Meaning: the amount of work a human must perform in interacting with the system. The workload can be measured by the number of hours of each task that is currently performed by a person. We can then classify the result as high, medium, or low workload. Quote from the paper [30]: "Other characteristics of the operator that are of interest are his perceptions of risk and own workload, his skill level, his performance level (decision accuracy), and his level of self-confidence."

Explanation: One person has a workload of 36 hours (high), while another has a workload of 4 hours (low). Higher workloads could demand higher automation to expedite work.

5) ENVIRONMENT

Variability [45]. Meaning: Variability refers to how the environment changes with time and ranges from unchanging (low variability or highly predictable) to highly dynamic (high variability or unpredictable). Quote from the paper [45]: "This dimension determines whether automation is applicable: automated systems cannot function well in dynamic environments, but humans can."

Explanation: if the environment is highly predictable, full automation is preferred. Where the environment is highly unpredictable, less automation and more human involvement are preferred.

B. CAPTURING CONSTRAINTS

As we depict the known factors and their relationship with LOAs, we also consider how different factors (two or more factors combined) can affect LOAs. To investigate the effects of the combination of factors, we turn to the analysis of taxonomy proposed by Simmler et al. [23]. This taxonomy does not offer a level for "manual execution" as it is only intended to classify human-machine collaboration. The taxonomy proposed by Simmler et al. includes the following levels:

- Level 1: Offers decisions. Technical component suggests options, and the human decides
- Level 2: Executes with human approval. Technical component acts after human approves
- Level 3:Executes if no human vetoes. Technical component acts unless human vetoes
- Level 4: Executes and then informs. Technical component acts independently, and human is informed about the actions carried out
- Level 5: Executes fully automated. Technical component carries out actions independently without informing human

In this taxonomy, if the first and lowest level of autonomy (Level 1 - Offers Decisions) is selected, the agent must have the capability of making recommendations and receiving feedback. In addition, transparency, traceability and predictability are requirements for system quality. The last and highest level of automation (Level 5 - Executes fully automatically) can be selected if the system has nontransparent and undetermined quality features. Data gathering, interaction with other agents, and adaptability are some of the agent's capability features that must exist to meet the requirements of level 5. The authors consider the ability to learn through machine learning algorithms and connecting to the Internet as optional features for this level. The following constraints are examples that we captured from these rules and that we should consider if Simmler's taxonomy is selected.

In Level 1, according to the authors, a given input should always lead to a specified output. There should be complete transparency in how the system reaches that output. The system is fully traceable and predictable, with no ability to learn. For example, calculators work on this level. Therefore,

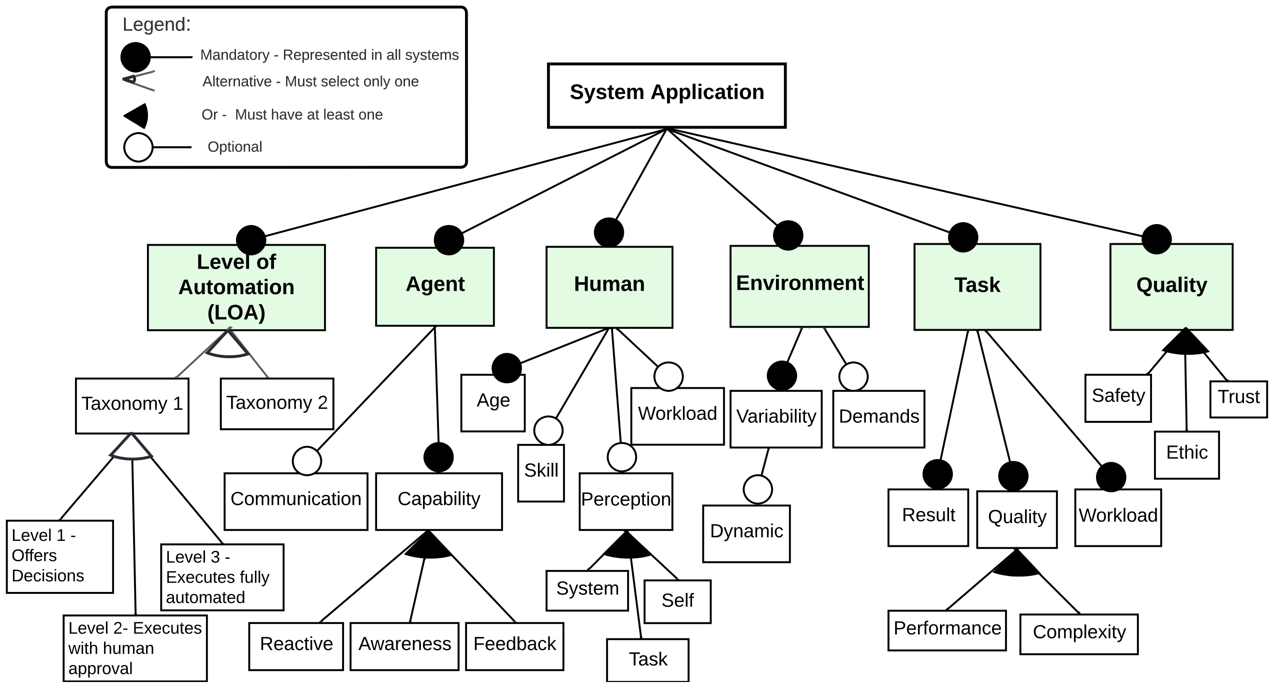

FIGURE 2. **LOA variability model in autonomous systems: An adaptable feature diagram.**

we can say that with the highest transparency and highest predictability, an automation level is set to 1. In the following representations the symbols ⇒, ∧, ∨ and ¬ mean implication (if…then), conjunction (and), disjunction (or) and negation (not) logical connectives, respectively.

High Transparency ∧ *High Traceability* ∧ *High Predictability* ⇒ *Level 1*

If a system is not transparent, this means not every step is predefined and traceable. The system holds back information and moves from the input to the output, altering its manners and impacting the observer's perception. However, the output can still be determined. An example is a system that weighs many parameters before deciding. Therefore, the authors define this combination of factors as leading to level 2 automation.

Low Transparency ∧ *Medium Traceability* ∧ *Medium Predictability* ⇒ *Level 2*

A system classified at level 5 is not transparent. An input might not lead to the same output every time, and the human cannot access how the system has reached that specific output. Systems based on machine learning algorithms and connected to data sources on the internet are examples of such systems. These systems have very low transparency and predictability while having high interaction with multiple data sources and high adaptability.

Low Transparency ∧ *Low Predictability* ∧ *High Integration* ∧ *High Adaptability* ⇒ *Level 5*

Next, we describe the representation of the identified factors and how levels of automation can vary according to these factors.

VI. REPRESENTING LOA FACTORS VARIABILITY: FEATURE MODEL

The first step to achieving variability in a system is understanding and representing variability in its application domain. Given the diversity of current intelligent systems, our goal is to propose a flexible solution that may be used for several situations rather than one unique problem. Our approach incorporates Feature-Oriented Domain Analysis (FODA) [46] to represent the system variability using a feature model (FM). FMs are primarily used in domain engineering to represent common and variable characteristics to maximize the reuse of software features or components [47]. This tree-like notation (FODA) is typically used in software variability management to provide a visual hierarchy of features [21], [22], and has also been used to compare the design space of technologies such as model transformations [48], conversational AI systems [49], and asset management in Machine Learning [50].

Our study adds to the body of knowledge by providing a feature-model-based depiction of the factors affecting the degree of automation in autonomous systems. This paradigm can be used to develop autonomous systems that interact with people. Our goal is to represent and model the variability of factors that influence levels of automation and how the interaction of these factors influences levels of automation. Although other notations to represent variability exist, such as the Cardinality-based Feature Model (CBFM) or Common Variability Language (CVL), the original FODA's notation can effectively express commonality and variability. FODA notation represents a feature, mandatory, optional, AND, XOR, and constraints [47]. As a result of this factor mapping, we propose a model diagram represented in Figure 2.

The factors that were identified in our literature review are shown in this diagram. For the sake of simplicity, not every identified factor is presented in the diagram. We illustrate the primary factors: Agent, Task, Human, Environment and Quality. We added the representation of the Level of Automation taxonomy, which is also affected by the variability of LOAs. The LOA and the primary factors are mandatory features, making them required to design adaptive automation systems. As shown in Figure 2, our feature diagram specifies some rules that must be respected independently of the application and the taxonomy, such as 1) for every task, it is necessary to specify at least one quality criterion; 2) every agent must have at least one capability, such as reactivity and awareness; and 3) every human must have a role in the system. In this approach, researchers can use our model regardless of the LOA taxonomy. Additional rules to control the relationship between the factors will be dynamically loaded based on the selected taxonomy.

Feature diagrams can have constraints associated with them. In our case, we can use at least three types of constraints. The first type of constraint is like the ones we have shown in the previous section. This type of constraint represents how the features (or factors) can impact the level of automation and can be represented in general as expressions of the form:

$\boxed{\Sigma \Rightarrow \textit{Level X}}$

where Σ is an expression involving one or more features. An example like the constraints represented in the previous section is:

$\boxed{\textit{High Transparency} \wedge \textit{High Traceability} \wedge \textit{High Predictability} \Rightarrow \textit{Level 1}}$

The second type of constraint represents how the LOA can impact the agent behavior, that is, given an LOA, specific agent capabilities can be provided. This constraint can be represented in general by:

$\boxed{\textit{Level X} \Rightarrow \Theta}$

where Θ is an expression involving one or more features. An example of this type of constraint is:

$\boxed{\textit{Level 3} \Rightarrow \textit{Detect warning signs} \wedge \textit{Inform warning signs}}$

The third type of constraints represents how some features can impact other features and can be represented by:

$\boxed{\Sigma \Rightarrow \Theta}$

where Σ and Θ are each expressions involving one or more features.

VII. INSTANTIATING AND DEMONSTRATING VARIABILITIES

This section presents examples of the proposed LOA factors model's instantiation in two domains. The purpose of instantiation is to clarify the model's purpose and rationale and the complexity of the interaction between factors. The first example presents a scenario in the development of automated vehicles, and the second is an example of customer service chatbots.

A. SCENARIO A: AUTOMATED VEHICLES

In the development of Autonomous Vehicles (AV), vehicles can execute a broad range of tasks without human intervention or partial intervention, such as controlling the car's speed and switching lanes [51]. There has yet to be a consensus about the complete autonomy of these vehicles, as some researchers have proposed strategies for controlling their level of automation according to their location (e.g., highway, commercial street, residential street), application concerns (e.g., safety, security, improvement in fuel economy); or even to the driving style (e.g., aggressive, normal, calm). Recent research has investigated enhancing the control and decision-making capabilities of autonomous or semi-autonomous vehicles, enabling them to efficiently navigate their trajectories while avoiding obstacles [52], [53], [54].

Ribeiro et al. [51] present a literature review about the requirements involved in the development of AVs, identifying different types of autonomous vehicles with varying levels of autonomy. Based on this literature review, we identified and classified the factors that can make AVs assume different degrees of autonomy. Further, we represent these factors as features, making it possible to investigate and model their dependencies.

- Quality
  - Safety: Because of the auditing and certification process, there are a set of safety-related ISO standards usually addressed by AVs, such as ISO 26262, which handles possible hazards caused by the malfunctioning behavior of electrical or electronic systems
  - Security: protection against cyber-attacks which can expose personal information on other connected devices
  - Usability: functions that facilitate the interaction of the user with automated functions, autonomous taxis, or family vehicles (for children, the elderly, or people with disabilities)
  - Accessibility: A car that can be operated independently, even by those who cannot drive a conventional vehicle
  - Law Compliance: complying with federal and state laws in a specific region
  - Transparency: the system requires transparency in the process owing to the possibility of an accident or similar situation that needs verification
  - Trust: Society and government that create and monitor regulations, as well as the driver or passenger, must be able to trust a vehicle
  - Environmental impact: the driving style can impact vehicle emissions and energy consumption
- Task
  - Quality:
    - Risk: driving has some eminent risks that vary according to the environment (e.g., the risks involved in a residential area differ from the risks

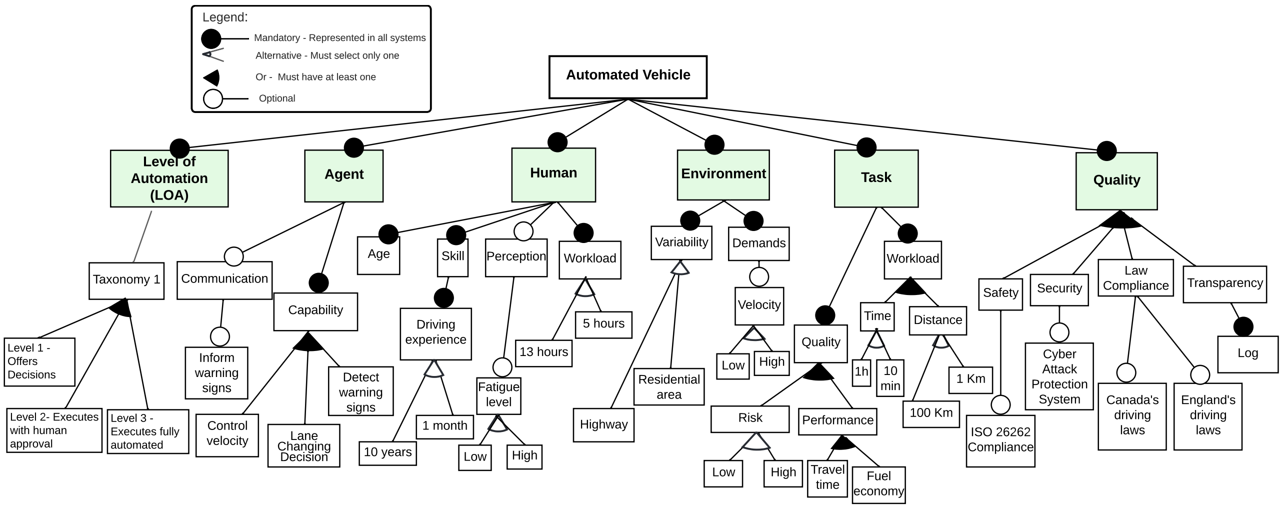

FIGURE 3. Scenario A: LOA variability model in autonomous vehicles.

on the highway; in some regions, the risks vary with the weather)

  * Performance: the performance of the task may be measured based on a reduction in travel time, traffic deaths, or in exhaust emissions, or an improvement in fuel economy

- Workload: the driving activity may be associated with some workers, such as taxi and truck drivers. Thus, the task's workload may vary according to the distance and local information, such as local traffic or weather

• Agent
  - Communication: some AVs have heads-up displays to show information to the driver. Vehicles should be able to communicate with other vehicles
  - Safety: protection against faults at the system level, including hardware and software
  - Capability: AVs may have many behaviors, such as controlling the car's velocity, lane change warnings, and obstacle avoidance

• Human
  - Skill: time of driving experience measured through the driving license years
  - Workload: The hours a driver can drive in a day vary according to local laws. In Canada, for example, a driver can only drive up to 13 hours daily
  - Perception (Reliability): Fatigue level

• Environment
  - Variability: The environment has dynamic properties related to mobile objects, such as pedestrians and other cars, and static properties related to roads, traffic signs, and weather [55]. Therefore, the vehicle needs to be aware of its environment
  - Demands: Federal and state laws demand different safety requirements, and the weather, road type, and warning signs demand different driving behavior. For example, highways demand high speed, while residential areas requires low speed. However, even on a highway, a crossing sign warns drivers to slow down and be prepared to stop

After identifying the factors impacting a vehicle's levels of autonomy, we present a feature model in Figure 3 to explore designing AVs with different levels of automation. Based on this figure, we show below some examples of how these factors can impact the level of automation and how the LOA can impact the agent behavior:

Residential area ⇒ Level 1 (Offers Decisions)
Highway ∧ Low risk ⇒ Level 3 (Fully Automated).
Highway ∧ High risk ⇒ Level 2 (Executes with Human Approval).
Highway ∧ High risk ∧ High fatigue ⇒ Level 1 (Offers Decisions).
Level 1 ⇒ Detect warning signs ∧ Inform warning signs
Level 3 ⇒ Control speed ∧ Decide about lane changing

Based on these dependencies, we can consider vehicles that can assume more than one degree of autonomy, selecting the most appropriate level for each situation. For example, a car controls the velocity on highways but returns control to the driver when it approaches residential areas. In such an example, for residential areas, the vehicle will have a lower level of automation, making the driver responsible for the speed control. At this lower level, the car cannot control its own speed, but it can provide information about warning signs, such as school crossing and speed limit warning signs.

B. SCENARIO B: CUSTOMER SERVICE CHATBOTS

Chatbots can significantly support business operations. For example, in interactions with customers, 24/7 availability and machine learning capabilities can provide customers with automatically generated personalized responses based on their needs and hopefully resolve issues faster [56]. Customer service chatbots can replace FAQs, provide

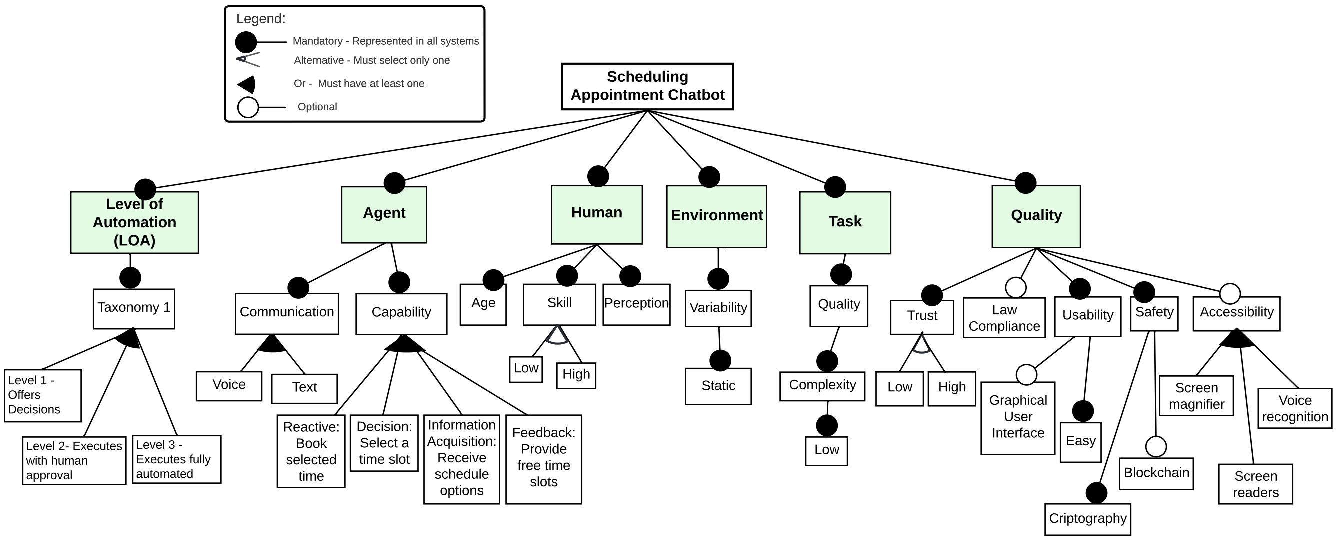

FIGURE 4. **Scenario B: LOA variability model in customer services chatbots.**

extensive information about a product, schedule appointments automatically and perform many other useful functions. Chatbots can set up and change customer appointments for all business types, from healthcare organizations to home maintenance companies. Chatbots are connected to the company's

calendar and can educate customers about personnel availability and available timeslots, enabling them to make appointments without contacting humans at "front desks." According to a 2019 survey [57], customer service chatbots must be equipped with the following:

- Ability to provide personalized responses to each customer regardless of whether it is a FAQ
- Understand the customer's context
- Provide real-time insights to agents to resolve inquiries quickly
- Understand the value of the customer and their history of transactions/interactions with the company
- Identify actions based on customer responses
- Lead users through an automated dialogue to clarify the intent

Considering a scheduling appointment chatbot as our second use case and automatically booking an appointment as the fully autonomous response of these systems, the following factors would influence the LOA of such systems:

- Quality
  - Trust: Users must trust the systems, however not as much as health care system patients
  - Ethics and Law Compliance: No law compliance is needed to book appointments, however, patient data should be secure in case the system is scheduling medical appointments, for example
  - Usability: Interfaces must be comprehensive and easy to use, as this system will be used by non-technical users
  - Safety: Safety of the system is important; however, it does not need to be the reason for high investments
- Task
  - Complexity: This system does not deal with complex tasks
- Agent
  - Communication: text- or voice-based chatbots
  - Safety: standard data protection suffices
  - Capability: to understand the client's schedule request
  - Domain: no domain-specific requirement to book appointments
- Human
  - Age: the system might need adaptation for the elderly, accessibility
  - Skill: Users do not need technical skills to interact with this system
  - Perception (Reliability): Users must rely on the system
- Environment
  - Variability: The system does not need to be aware of environmental changes, therefore, can potentially be static

We mapped these factors as features in Figure 4. Handling different feature combinations, we can explore some relations between the level of automation and the behavior of the scheduling appointment chatbots, as follows:

Level 1 $\Rightarrow$ *Provide free time slots to the user* $\wedge$ *Book the selected time.*

Level 2 $\Rightarrow$ *Select a time slot for the user* $\wedge$ *Book a time slot after the user's approval.*

Level 3 $\Rightarrow$ *Select a time slot* $\wedge$ *Book a time slot for the user.*

In the same way, we can also explore some of the characteristics that the system must have to accomplish the different levels of automation:

Feedback (provide free time slots) $\wedge$ *Book selected time* $\wedge$ *Graphical User Interface* $\Rightarrow$ *Level 1*

Decision (Select a time slot) $\wedge$ *Receive user's approval* $\wedge$ *Graphical User Interface* $\Rightarrow$ *Level 2*

Decision (Select a time slot) $\wedge$ *Book selected time* $\wedge$ *Trust (High)* $\Rightarrow$ *Level 3*

As shown, if the system operates at levels one or two, the interaction between the agent and the human is higher, so the system must provide a graphical user interface to meet the mandatory requirement of easy usability. In the case of having a chatbot operating at the highest level, a robust interface is unnecessary (e.g., a command line interface), as the chatbot can make decisions and select the best time for the user autonomously. On the other hand, the level of trust in the system needs to be higher.

VIII. DISCUSSION

To date, studies that outline factors that affect automation level decisions are scarce. However, scholars have attempted to identify various levels of automated taxonomies, each having a particular function. These definitions can extract the factors that authors use to determine the level of automation at which the system and its specific tasks should operate. These taxonomies often cover a spectrum spanning from fully manual to completely autonomous.

Regarding the identified factors, quality factors are mentioned, as well as system and task factors. For the system, quality is usually acquired with testing and process verification. Task quality factors are different in that they are related to the performance of the execution of a task or the task's complexity. Situation awareness is also related either to a task or a system. While a person can be "situationally aware" through knowledge, experience, and human sensory and decision-making abilities, a system can be "situationally aware" through sensors and contextual information. Likewise, according to Villani et al. [32], demographics including age, are essential factors since they allow, for instance, customizations specifically targeting elderly or inexperienced system operators, supporting them to achieve tasks they would otherwise be unable to perform.

These findings support understanding the factors determining whether tasks should be more or less automated and to what extent. Therefore, it is conceivable to assume that systems that anticipate various LOA might also be built to recognize the variables that impact the amount of automation and adapt as necessary. For example, an autonomous car has categories for how aggressive the driving might be. This determines, for instance, how distant another car must be for the autonomous car to merge into a lane. The more aggressive the driving mode is, the shorter the distance between the autonomous car and the other car when merging lanes. Although the action to merge lanes is autonomous, the user (driver) must manually set the aggressive mode category. Suppose we were to analyze the factors that could influence the driving mode, such as weather, total driving distance, drivers' agendas (how fast they need to get somewhere), who is driving the car or even the landscape of the road. In that case, the driving mode could be set automatically without manual input for most of these factors.

The development of a software engineering discipline that addresses autonomous system design and identifies factors that influence the variance of levels of automation in autonomous systems could potentially significantly impact the field of autonomous systems and artificial intelligence research. This could lead to more efficient and effective design and development of autonomous systems' software and better understanding and management of the relationship between humans and machines in such systems. The findings suggest that a software engineering approach that considers the factors determining the appropriate level of automation (LOA) for a task can be beneficial. Such an approach would allow for the development of systems anticipating various LOA and recognizing the variables that impact the amount of automation required. This approach can lead to the developing of autonomous systems that can adapt to changing conditions and user preferences, thus increasing their effectiveness and efficiency.

In AI, this approach can lead to the development of AI systems that can learn from experience and adapt to changing conditions. By considering the factors that influence the appropriate LOA for a task, AI systems can be designed to be more flexible and adaptable. Additionally, this approach can lead to the development of AI systems that can be designed to operate at different levels of automation depending on the context, thus increasing their usability and applicability.

IX. CONCLUSION

In this study, we aimed to answer the following research question: Which factors affect the variance of levels of automation in autonomous systems? We performed a systematic literature review to identify the factors related to varying levels of automation. We describe the methodology of the approach and list all the identified factors in a table, linked with their corresponding source article(s). We then provide a categorization of the identified factors that affect levels of automation in systems. We categorize these factors into five main categories: Quality, Task, Agent (System), Human and Environment factors. To continue the work, we refine these factors by demonstrating how systems can capture and embed them in their operation. We also introduce a representation of these factors and their variability, demonstrating the relationship of factors with specific levels of automation. Lastly, we demonstrate how these factors can be applied to two different scenarios with illustrative examples. Prior studies have recognized the value of research into the definition of the taxonomies of LOAs. This research complements taxonomy research, by investigating the factors that affect the choice of one level of automation over another, contributing to the development of adaptive autonomous systems independently of the LOA taxonomy being used.

The present results are significant in at least two major respects. First, it highlights the existence of these factors, categorizes them and presents how a combination of different factors can influence how intelligent autonomous systems work. We also demonstrate how systems can capture factors and systemize the process of implementing such factors. Finally, we achieve system adaptability and characterization by identifying and representing these factors as feature models.

Our work also raises questions for future research. One of these questions concerns the challenges of implementing these factors in autonomous systems. How can these factors be implemented in autonomous systems while still ensuring that the systems remain safe and reliable? Another important area of research is validating the proposed approach by implementing real-world autonomous systems and testing them under various conditions. Future work can explore using the proposed model to assess the automation of problems in specific fields, such as software engineering and other domains. We also aim to implement this model, investigate its contribution to different application scenarios in conversational agent architectures, and investigate which taxonomies are ideal for conversational agent solutions. Keeping a history of the factors that impact specific tasks can also be used to measure the performance of the task and evaluate the selection of the level of automation. Additionally, such models could potentially contribute to proving the decisions made.

In conclusion, this study contributes to the development of adaptive autonomous systems by identifying and categorizing the factors that affect the choice of one level of automation over another. By using the identified factors and their variability, software engineers can design autonomous systems that can operate more effectively in various conditions. The results of this study have practical implications for the development of autonomous systems and provide a foundation for future research in this field.

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