Adaptive Autonomous Underwater Vehicles: An Assessment of their Effectiveness for Oceanographic Applications

Abstract**—** Autonomous underwater vehicles (AUVs) are practical tools for ocean observation. However, they tend to operate in an automatic rather than autonomous way. This reflects the attitudes and behaviors that individuals and organizations share when adopting new technology in this industry. This paper clarifies the factors that are preventing one important aspect of autonomy - adaptive mission planning (AMP) - from transitioning from research to commercial and bespoke AUVs. Twenty-five experts comprising AUV developers and users, with combined 237 years experience, provided their views in a structured survey covering several different hypotheses. There is insufficient evidence to determine clearly a single reason for failure to adopt AMPs but a primary cause is the paucity of demonstration trials. This view is irrespective of participants' years of experience. Managers, Engineers and Technologists agree on the two most likely causes for failure to adopt AMPs. However, the differences between the assessments provided by Researchers and these three professional groups are statistically significant, with p value < 0.005. For Researchers, complexity is one of the two most important inhibitory factors. We present recommendations to support the integration of AMP into AUVs substantiated by recent examples where government, industry and researchers have developed and tested AMPs.

Index Terms**— autonomous underwater vehicles, adaptive planning, autonomy, gliders, mission planning, risk, precision, positioning**

Managerial relevance statement

The adoption of adaptive autonomous underwater vehicles (AUVs) has reached a chasm. In the last 20 years, investment and subsequent AUV developments led to new platforms that can operate for periods of 6 months rather than a few hours, to dive to 6000 metres rather than to 100 metres. However, to this date AUVs still operate in an automatic manner. We show that the reasons for not adopting adaptive AUVs is socio-technical problem; where researchers, technologists, managers and engineers have different understandings of the reasons why this technology has not been adopted. Understanding this is key for identifying actions that will enable this technology to cross the chasm between innovators and early adopters.

A survey was conducted to elicit from engineers, scientists, researchers and managers the key reason for failing to adopt adaptive AUVs for oceanography. As result of this study we have identified key actions. We hope that this paper will make the following contributions to practice: 1) Criteria for evaluating the performance of adaptive AUVs; 2) Identification of a risk analysis gap and efforts that must be made in this area; 3) A process for training engineers and scientists in this community; and 4) Recommendations for engaging early adopters.

I. INTRODUCTION

In the 1990s, research centers started the development of autonomous underwater vehicles (AUVs) for sea bottom survey and science [1]. These organizations have demonstrated the benefits of using AUVs to gather data and conduct tasks that could not have been done in any other way [2][3][4][5]. Arguably, the most impressive deployments were those in extreme environments such as under ice where the seabed was also an important boundary, e.g. [3]. An early deployment under ice requiring a high degree of situational awareness was that of the cable-laying Theseus AUV, from Jolliffe Bay, Canada in April 1996. Deployed through 1.7m thick ice, after a 175 km mission the vehicle parked itself under the ice for recovery within range of a remotely operated vehicle [6].

While there have been significant developments in AUV technology to take some vehicles beyond the capability of automatons navigating between pre-programmed waypoints [7] the level of intelligence in AUVs used in oceanography has remained relatively unchanged over the previous two decades. In contrast to what has occurred in other fields of robotics such as space, aeronautics and automobiles most oceanographic AUVs still follow pre-defined mission plans, making little or no use in real time of the data they are gathering except for their position and proximity to boundaries.

Meanwhile, there are numerous applications that could benefit if a greater degree of autonomy could be shown, for example using measured data to track the source of dynamically evolving features such as a plume or an ocean salinity front. Our review shows that while several solutions for adaptive mission planning (AMP) have been proposed [8], AMP technology for AUVs is yet to be adopted by the wider oceanography community.

In order to identify remedial actions this paper clarifies the reasons why AMP has not yet been adopted by AUV users within the oceanography community. Twenty-five experts on AUV technology completed a survey to capture their confidence in a given potential root cause. In addition to a quantitative analysis of experts' assessments, a detailed analysis of the experts' rationale for their assessment is presented. This allowed us to establish whether or not the expert was subconsciously introducing bias. The professional roles for experts were considered as well. In the relatively few examples of research where AMP has been implemented in the field, it has been broadly noted that engineers have a different perspective than scientists in the development and use of AMP for oceanographic applications [9]. Our study also examines the differences in perspective between engineers, scientists, researchers and managers.

This paper is organized as follows. Section 2 provides a background on AMP. Section 3 identifies concerns and issues associated with AMP. The probabilistic tree used for helping the experts decide on which are the main causes for failure to adopt AMP is introduced in Section 4 and the diagnosis model is covered in Section 5. General analysis of the expert assessment and root cause analysis are covered in Sections 6 and 7 respectively. Our recommendations for engineering management are presented in Section 8, limitations of this work are in Section 9 and the main conclusion is in Section 10.

II. BACKGROUND ON MISSION ADAPTIVE SYSTEMS

An early architecture proposed for adaptive robotic systems was the sense, plan, act (SPA) framework [10]. A recent example being for collision avoidance where the reactive layer provides a fast emergency response [11]. The adaptive Observe Orient Decide Act (OODA) machine proposed by Boyd [12] was adopted by Patrón et al. to define a fault tolerant adaptive AUV mission planning system [13]. Another frequently cited approach is the Perception; Situation Evaluation; Decision; Action architecture [14]. These architectures specify the components that make the mission system adaptive and how information and actions are communicated between them.

Another approach uses MOOS-IvP, a behavior based mission management system designed to resolve optimal action for an autonomous system with competing subsystem goals. It consists of two modules: a Mission Oriented Operating Suite (MOOS) which enables communication between software modules and a module that resolves competition between different behaviors by performing multiple objective optimization on their collective output using interval programming (IvP). Among other examples, this framework was used for establishing communication and distributed control for a heterogeneous fleet of unmanned vehicles in a large multi-institution experiment [15][16]. Control of multiple assets was required with the intent to improve survey outcomes by reducing human operator burden. The month long Adaptive Sampling and Prediction experiment conducted in Monterey Bay in 2006 involved navigation synchronization within two homogeneous sets of gliders, Slocum and Spray. Each set of gliders was given a predefined survey trajectory to navigate, the individual gliders within each set would report in periodically to a base control station and receive an updated mission plan in order to act in coordination with the other gliders within its group. In this way, multiple vehicles could maintain optimal survey trajectory spacing and a degree of temporal correspondence in the face of changing ocean currents [17].

In an example of using an adaptive mission planning approach developed for non-marine environments, T-REX was ported to AUV use. Descending from the National Aeronautical and Space Administration temporal constraint-based planner EUROPA2 [18] the T-REX coordinator is made up of many semi-independent Sense Plan Act (SPA) controllers, termed Teleo-Reactors [19].

The first deployment of the Monterey Bay Aquarium Research Institute's Dorado AUV with T-REX was in the Monterey Canyon in January 2008. The aim of this deployment was to conduct an Intermediate Nepheloid Layers (INL) survey, collecting samples of plankton from thin layers whose depth and extent vary with the physical ocean conditions. Subsequent surveys were conducted with a revised adaptive behavior to enable sample collection closer to the center of the INL [20]. For decision-making, T-REX used the Hidden Markov Models (HMM) machine learning technique [21]. The algorithm decided when to open the samplers, based on the estimated chance that the INL was likely to be observed, where the accepted likelihood was 0.45. Results showed that the vehicle successfully changed its course and depth in order to maximize the chances of capturing INL. Like MOOS-IvP, T-REX has been applied in cooperative vehicle applications. It has been used on an AUV in conjunction with a mixed initiative planner, EUROPtus, to enable AMP amongst a heterogeneous set of autonomous vehicle (underwater and aerial) [22].

A chemical plume tracing AMP capability was implemented on a REMUS AUV that was designed to mimic an olfactory type response and home in on the plume source [23][24]. A more generalized approach to feature tracking was implemented where MOOS-IvP was used to successfully demonstrate tracking of the thermocline using an Ocean Explorer AUV during the Generic Littoral Interoperable Network Technology (GLINT) sea trials in 2009 [9].

AMP was implemented on two Ocean Explorer AUVs for a littoral monitoring experiment. While it was not directly an oceanographic application, the AUVs were able to process an acoustic signal using their onboard passive acoustic system in real-time in order to navigate toward a stationary and a moving acoustic source as part of the GLINT 2010 sea trials [25]. In a somewhat similar and recent work using active acoustics (fisheries echosounder) integrated on a REMUS AUV, AMP was implemented to enable the AUV to track, characterize and quantify squid stock in the Atlantic Ocean [26]. The AMP technology was tested and implemented; however, it was only fully operational for one dive out of a total of 50 missions. This is an interesting AMP use case where the technology was developed and ready for AUV operations, yet it only saw limited use. Primary causes for the limited implementation of AMP in this work are discussed in Section 9.

A real-time image classifier was developed and deployed on the Starbug AUV with the potential to adaptively sample marine habitat [27]. The classifier was shown to be robust and reliable for real-time operations in support of habitat classification; however, AMP was not implemented as part of this work. This is discussed later in Section 9. AMP was developed and implemented on board the Sirius AUV platform for habitat classification work in 2010 [28]. The AMP onboard real-time decision making was never fully deployed for several reasons and this is discussed in Section 9 as well.

This review shows that there have been a variety of approaches to adaptive sampling using AUVs by several research groups, in a variety of situations, with most being considered successful proofs of concept resulting in journal publications. Yet these methods have yet to become used widely and in some instances AMP was available for AUV operations; however, due to certain reasons it was not fully deployed or its application was limited.

III. PROBLEMS ASSOCIATED WITH MISSION ADAPTIVE SYSTEMS

In this paper we adopt the following interpretation of an adaptive AUV: An adaptive AUV is one that uses an on-board decision-making system to define the mission plan whilst on the go with the aim of optimizing feature detection and sampling. A paraphrased frequently used definition defines adaptability as the 'ability to adjust itself to its environment, learn from it and evolve.' We consider that, for now, learning is not a necessary feature of an AUV that can adapt to an environment.

There are a number of factors that could explain why a new technology, such as AMP, is not adopted widely, including:

- The product is not well understood. Adaptive systems consist of several algorithms that implement mathematical models. These models may be probabilistic or deterministic, or use a fuzzy logic approach; they may use optimization algorithms to inform decision-making. Those not familiar with the concepts implemented in these algorithms may experience some difficulty in adopting these systems.
- There is uncertainty as to vehicle behavior. Here the perception is that the vehicle will do something that is unexpected that can compromise data gathering, endanger the vehicle, or confuse or interfere with other water-space users.
- Financial costs of adaptive systems are too high. The costs include the development costs of interfacing the adaptive system with the legacy systems installed on the vehicle and the energy costs of operating the systems in real-time. If the adaptive system uses numerical prediction models on shore, these may need to be run on large computers, with consequent resource and staff costs.
- Benefits are too low. Adaptive systems deliver greatest value for very specific operations where the human operator input can be improved. If a given set of observations can be met with a conventional survey, then it becomes unnecessary to autonomously adapt the mission in real-time.
- Legal implications. The operation of autonomous underwater vehicles carries multiple risks: to the vehicle, to the environment, humans and marine animals. Operating in a given country's waters the operator must comply with the laws of the sea set by that country. This requires that the vehicle, mission location,

onboard sensors and type of operation must be notified to that country and appropriate approval sought from the competent authorities. The uncertain behavior of a vehicle with AMP may prove problematic for some authorities.

Different users and/or developers have different perceptions as to why there is a failure to adopt AMP more widely. The belief that one or more of the above hypotheses may provide an explanation can be captured probabilistically in terms of likelihood. In the next section we present a framework for eliciting the beliefs that each hypothesis may lead to failure to adopt the technology, thereby enabling the diagnoses of the root cause for failure to adopt mission adaptive systems.

IV. ROOT CAUSE ANALYSIS METHOD

The purpose of our investigation is to identify the key reasons for failure to adopt AMP in oceanographic applications that use AUVs. This is a decision problem with subjective uncertainty. Previously the authors used a type of decision tree (a probability tree) to help diagnose the most likely root cause for failure to establish communication with marine autonomous systems [29], which can lead to loss [30]. A probability tree approach also suits the problem presented in this paper due to the number of hypotheses that must be considered and the level of uncertainty associated with each hypothesis.

In section IV.A, we introduce the concept of a probability tree for structuring the decision problem of diagnosing the likelihood of each potential root cause for failure to adopt AMP. It is important to establish whether or not differences in assessments are statistically significant. Details of the statistical testing technique are given in section IV.B.

A. Probability Trees

A probability tree is a method used to model a sequential decision problem where each potential course of action has a likelihood of occurrence; Fig. 1 shows a generic structure.

Typically, probability trees are used to identify the option, or hypothesis, that maximizes expectation, deemed the optimal option. In root cause analysis, the optimal option is deemed the most likely root cause.

As shown in Fig. 1, for any decision problem, at level 1, there are *n* independent hypotheses, H_1 to H_n. The likelihood of each hypothesis being true is θ_1 to θ_n, where θ_1 is the probability of H_1 given D, and so on for the other options. This approach complies with the basic axioms of probability and also Bayesian theory. The hypotheses in any given level must be mutually exclusive and the likelihoods must add to 1.

It is possible that at level 1 the decision model does not capture the problem in sufficient detail. If so, Level 1 hypotheses are decomposed into Level 2 hypotheses. The decision-maker must consider what Level 2 hypothesis may lead to the consequence captured in the Level 1 hypothesis. In the second level, each hypothesis breaks into other potential decisions. For example decision H_1 breaks into m potential decisions, Ψ_1 to Ψ_m, with likelihoods α_1 to α_m.

The likelihood of a given path being true is the product of all likelihoods in that path. For example the likelihood of path (H_1, Ψ_1) is L(D,H_1, Ψ_1), calculated by multiplying the likelihood of each section, this is L(D,H_1) and L(H_1, Ψ_1). The probabilistic tree can be used for failure diagnosis by setting each failure path as a branch in the probability tree.

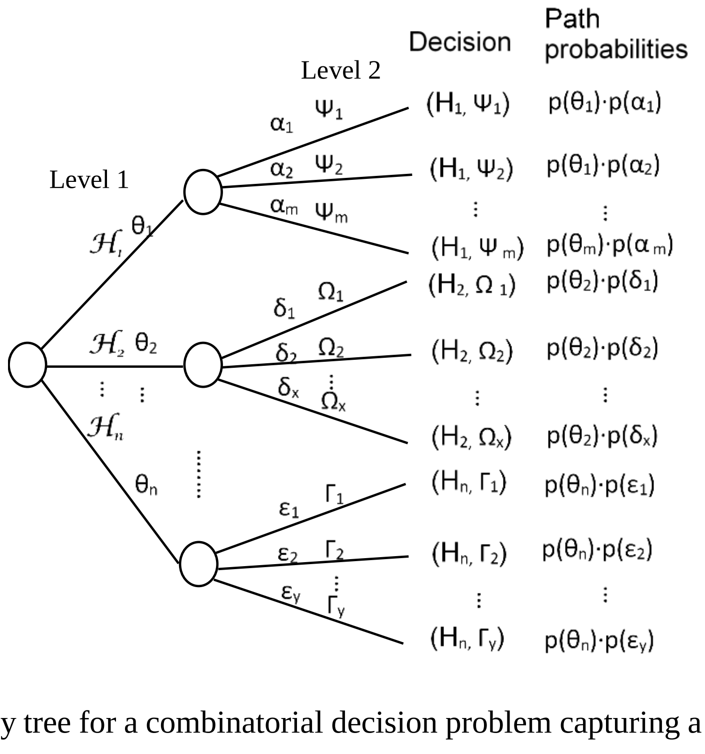

Fig. 1. Generic probability tree for a combinatorial decision problem capturing a sequence of two decisions. Adopted from [29].

B. Hypothesis Test

In this study, for each assessment, the experts were asked to provide confidence for a number of different categories – the hypotheses. Therefore, since we are dealing with category data, when comparing the assessments provided by two experts it is not possible to test the mean. However, it is possible to test the variation, or spread, of the assessments using the Chi-square (X^2) statistical test, Equation 1.

$$X^2 = \sum_{i=1}^{k} \frac{(f_i - e_i)^2}{e_i} \quad (1)$$

Where f_i is the observed frequency for category i; e_i is the expected frequency for category i; and k is the number of categories. The test statistic has a X^2 distribution with k-1 degrees of freedom [31].

When performing this test, we assume as the null hypothesis, H_0, that the difference between two populations is not statistically significant. The alternative hypothesis, H_1, is that the difference is statistically significant. A p-value lower than 0.05 is taken as sufficient evidence to reject the null hypothesis.

V. DIAGNOSIS MODEL FOR FAILURE TO ADOPT MISSION ADAPTIVE SYSTEMS

As shown above, a probability tree allows the diagnosis of the most likely path to failure. The difficulty is usually in designing a tree that represents accurately the problem of interest. In this section we review the probability tree defined for diagnosing failure to adopt AMP and provide details of the assessment process. Fundamental to the specification of the probability tree is the assessment of the likelihood of each branch of the tree leading to the respective consequence. In our study, 25 experts provided this assessment.

A. Probability tree for Failure to Adopt Adaptive Mission Planning Systems

A probability Tree is designed from left to right, starting from the End event – which is the failure for which one is looking to find the most likely root causes. It is important that all hypotheses leading to a given consequence are mutually exclusive.

At level 1, the causes for failure to adopt AMP are: failure to understand the technology; perceived uncertainty with regards to the vehicle response; technology is too expensive; benefits are not significant; or large uncertainty with regards to legal implications, Fig. 2. As there is a need for more detail, level 1 hypotheses are broken down into level 2 hypotheses in the case for failure to understand the technology, perceived uncertainty with regards to vehicle response and technology too expensive.

Failure to understand the technology breaks into technology is too complex or technology not well explained. It is possible that the AMP is not understood because it is simply too complex, for example, a complete understanding might only be possible across a multidisciplinary team of postdoctoral researchers spanning mathematics, computer science, control theory and software engineering. The counter argument is that there is a degree of complexity with all new technologies adopted by the AUV senior engineers and perhaps the AMP solution is not well understood because it is not well explained. To be understood, explanations need to draw upon core existing knowledge. However, methods used in current AMP systems are not taught at bachelor degree level – particularly to electrical or mechanical engineering students. Consequently, the argument is that the language and concepts used in AMP articles and presentations are not the most appropriate to an audience of AUV practitioners. For example, as befits a topic of active research, the inference method varies significantly between methods, however in several publications this distinction is not made explicit.

Many of the publications on the use of AMP are found in robotics or artificial intelligence journals and conference proceedings. This literature is not immediately accessible to engineers working in oceanography. Furthermore the language used in the literature may not be easy to understand for people outside the field. Thus the hypothesis that the technology is not well understood is further expanded: technology not disseminated widely enough and not explained appropriately.

Uncertainty with regards to vehicle response concerns a lack of confidence resulting from a possibly high level of uncertainty associated with the potential decisions taken by an AMP during live operations. It is very difficult, if not impossible, to completely predict (e.g. through simulation) all possible outcomes of an adaptive system once it is deployed in the field. This deterrent for failure to adopt this technology is further divided into insufficient demonstration and lack of risk assessment. Lack of risk assessment is subdivided into lack of documentation and lack of probabilistic risk assessment. An inability to formally quantify the likelihood of, or a level of confidence in, outcomes can make it difficult to justify the acceptance of risk for owners and/or developers and/or insurers who apply rigorous risk management regimes.

Cost is generally a key factor in any decision making process. Technology too expensive has two subcategories: development costs are not tangible and no pre-defined development lifecycle.

There remains uncertainty with the legal regulations and requirements concerning AUVs [32], let alone those using AMP. More recently Kirkwood has set out a series of legal questions in response to a number of incidents that occurred with MBARI’s Dorado AUV [33]. As vehicles become more autonomous and able to perform longer missions it is possible that vehicles will cross the water boundaries of different countries, giving rise to additional uncertainty as there is no specific provision for autonomous systems in international conventions such as the UN Convention on the Law of the Sea [32].

B. Expert Judgment Elicitation

The assessments for the likelihood of each hypothesis in the probability tree were elicited from 25 experts. The experts were selected based on an evaluation of expertise, reputation, availability and willingness to participate, understanding of the general problem area, and lack of an economic or personal stake in the potential findings [34]. Details about the experts’ background and expertise are presented in in Table A1. Our aim was to collect an overview of what the community perceives as being the root cause for failure to adopt AMP. Our aim was not to build consensus between experts.

The judgments were elicited using an online survey from October 2012. The link for the survey was emailed in conjunction with a text explaining the diagnosis model and a document containing describing the purpose of the study.

Of the 25 experts, twelve were employed by research laboratories, eight by private companies, and five by government institutions. The combined experience of the experts was 237 years, giving an average of experience of 9.5 years; the 25% quartile was 6 years whilst the 75% quartile was 12 years. With respect to their roles, three experts described themselves as engineers, four as technologists, four as managers and four as researchers. Ten experts had more than one role. The percentage of time that these experts spent in each role is shown in Fig. 3. Two of the experts with more than one role were predominately managers, two were predominantly engineers, and three were predominantly researchers. Three of the experts spent the same amount of time in two or more roles.

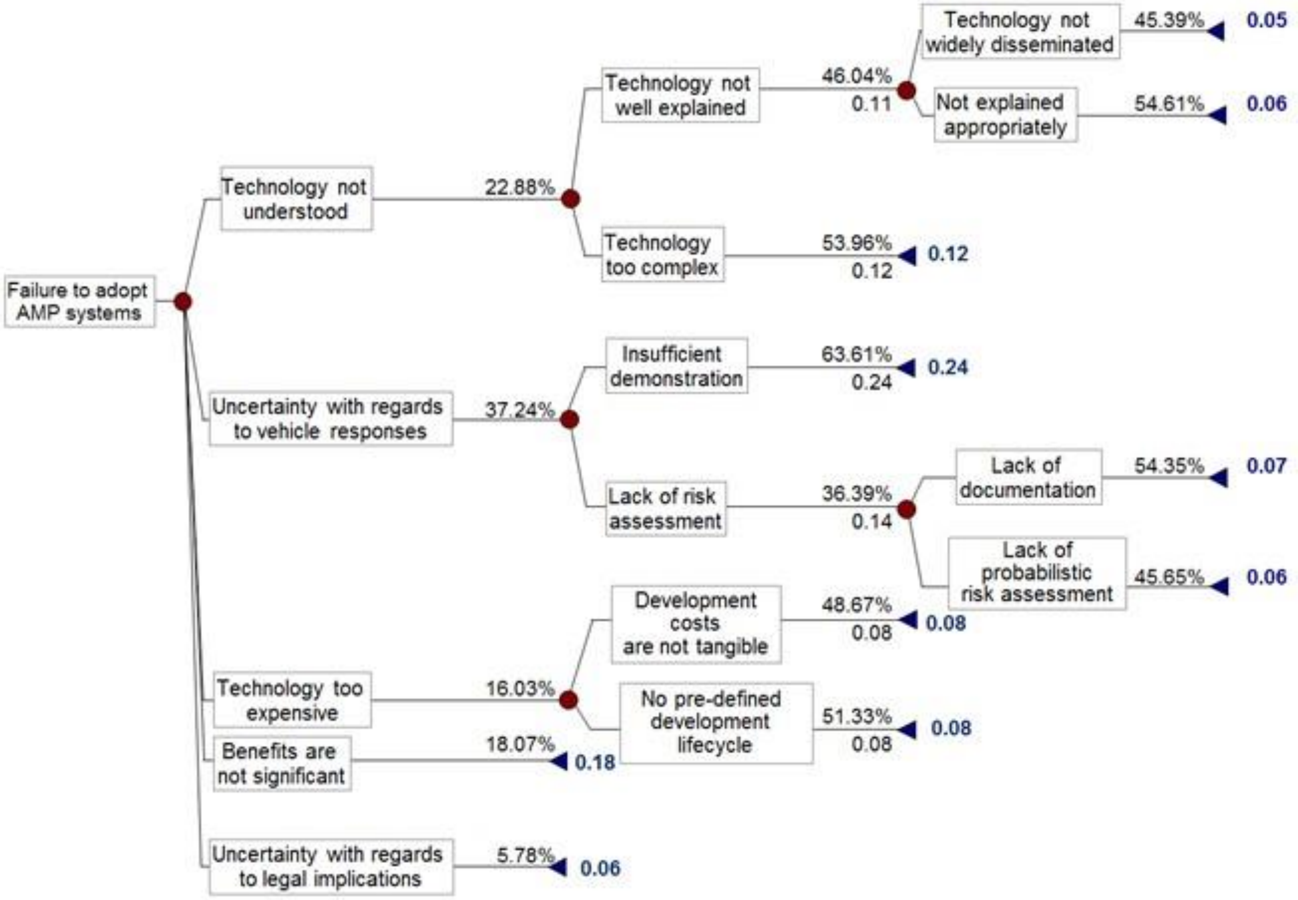

Fig. 2. Event tree of expert judgments into the failure to adopt mission planning systems. Red circles represent chance nodes and blue triangles represent root causes.

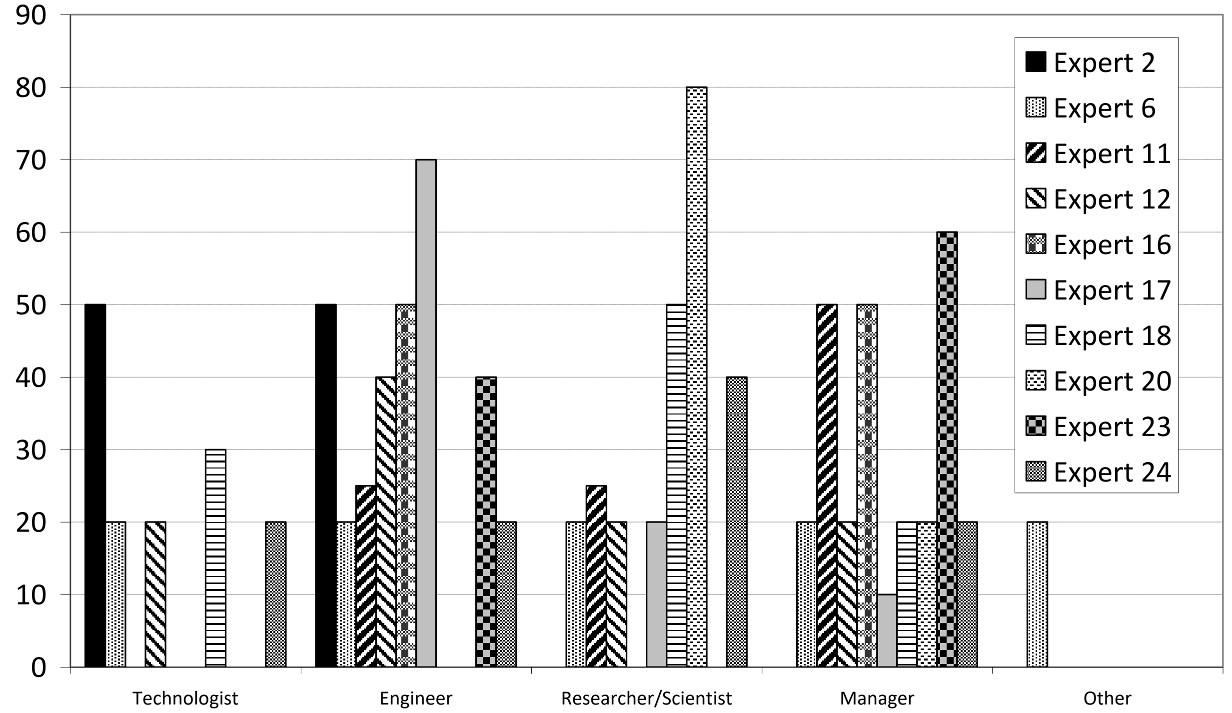

Fig. 3. Distribution of role for the ten experts with multiple roles.

According to their role, the experts are aggregated as follows, see Table A1 for more details:

- Scientists/Researchers: Formed of experts 7, 8, 13, 14 and 18. Expert 7 is a geologist, whereas experts 8, 13, 14 and 18 are researchers in robotics, combined experience of 59 years.
- Engineers: Formed of experts 1, 15, 17 and 22, combined experience of 37 years.
- Technologists: Formed of experts 3, 4, 9 and 19, combined experience of 26 years.
- Managers group: Formed of expert 5, 7, 21, 6 and 25, combined experience of 43 years.

To provide a different perspective for an analysis the experts can be rearranged in groups according to experience:

- Less than 5 years' experience: experts 9, 10 12 and 22.
- Experience between 5 and 10 years: experts 7, 21, 1, 4, 11, 18, 19, 20 and 23.
- Experience between 10 and 15 years: experts 2, 3, 8, 15, 16, 17, 24 and 25.
- Experience greater than 15 years: experts 5, 13, 6 and 14

VI. ANALYSIS OF EXPERTS' ASSESSMENTS

The expertise of the experts considered in this study covers a wide spectrum of knowledge and experience. The analysis of the experts' assessments was carried out by aggregating all judgments into a single judgment that represented the group view. However, by following this approach, it was considered possible that we may be ignoring significant differences of opinion. The average may not be representative of the group’s view when there is significant disagreement between experts' assessments. For this reason we asked each to provide the rationale for their assessments. This helped to identify whether or not the expert was introducing bias into their assessment. The analysis was carried out in two stages. First, histograms of the average of the expert assessments enabled us to visually deduce the hypotheses that experts think are the main root causes for failure to adopt AMP. Second, we assessed whether or not the differences in assessments were statistically significant.

A. Level 1 Failure Events

It is clear that there is a significant difference between the aggregated expert judgments; Fig.4 shows the average, the median, lower and upper quartiles of the confidence assigned to each hypothesis of level 1. Fourteen experts identified the perceived uncertainty with respect to a vehicle’s behavior as the most likely cause for failure to adopt AMP. The average gives a 37% confidence that this is the main cause for failure to adopt AMP; the median is 40%.

The standard deviation for failure to understand the technology is 21.7; 19.4 for perceived uncertainty with regards to the vehicle response; 15.2 for technology is too expensive; 20.6 for benefits are not significant and 7.32 for large uncertainty with regards to legal implications. This is indicative of the level of variability on experts’ perceptions about the importance of different root causes. Understanding this variability is important in order to derive recommendations for different actors in the adoption process. Next, we assess whether differences between professional roles contribute to this variability.

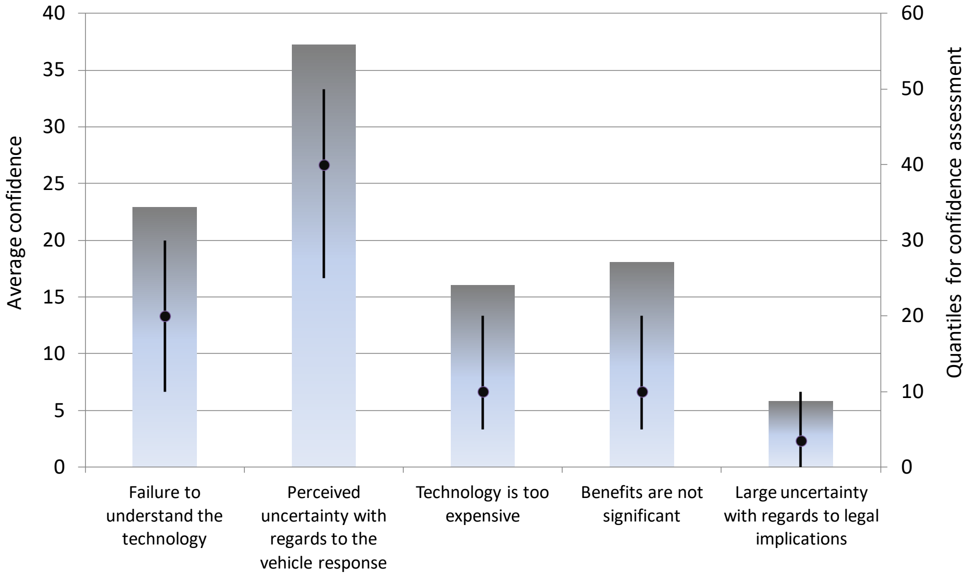

Fig. 4. Average of the assessments provided by all 25 experts. The bar charts (left axis) show the mean of the expert assessments for all hypotheses for level 1. The stock chart (right axis) shows the median, lower and upper quartiles.

1) Assessment analysis by professional role

To assess whether or not differences between groups of experts defined by professional role were statistically significant we used the X^2 test, Table I, where the problem presents 12 degrees of freedom. The X^2 test shows that for managers and technologist the difference in the mean of the assessments provided for level 1 is not statistically significant, but they are statistically significant for the other groups. For example, the p–value < 0.005 for the X^2 test between the engineers and managers indicates that the difference between the means provided by these experts is statistically significant.

All experts groups considered uncertainty with regards to vehicle response as the main cause at level 1 for failure to adopt AMP. The main difference between groups of experts is their assessment of the second most likely cause. Whilst researchers and engineers believe that technology is not understood is the second most likely root cause managers and technologists, believe that it is benefits are not significant – with managers having the same assessment for benefits are not significant and technology too expensive.

TABLE I

P-VALUES FOR THE X^2 STATISTICAL SIGNIFICANCE TESTS FOR LEVEL 1 ASSESSMENTS. DEGREES OF FREEDOM IS 12.

p-value	Managers	Technologists	Engineers	Researchers
Managers	-	0.286	< 0.005	< 0.005
Technologists	0.156	-	< 0.005	< 0.005
Engineers	0.0443	0.0435	-	< 0.005
Researchers	< 0.005	< 0.005	< 0.005	-

The high confidence that researchers/scientists assigned to technology is not understood is a result of the assessment provided by expert 7 as this expert assigned 100% to the this hypothesis. The other experts in the researchers group have nearly evenly assigned assessments between the two hypotheses technology not understood and uncertainty with regards to vehicle response.

The average assessments that these experts have given are 38% for technology not understood and 43% to uncertainty with regards to vehicle response. Researchers/scientists were divided between these two hypotheses. Expert 8's views on the importance of knowing what the vehicle decides to do typifies these concerns: “There are other factors I believe: 1- it's a new technology, and just like any technology adoption is not immediate; 2- It's one thing to have a framework to adjust the plan, but another to decide what a better alternative is - how is the vehicle to know that plan B is better unless it 'understands' its environment.”

Lack of understanding can be in terms of implementation as well as in terms of the theoretical framework. Expert 14 suggested: “The problem of understanding how adaptive mission planning software interacts with legacy code and also with error recovery procedures is not yet well understood. More experimentation is needed.”

Expert 18, who assigned 40% to failure due to poor understanding and 30% to the uncertainty with regards to vehicle response commented: “The fundamental issue is that of poor understanding of what 'autonomy' (especially AI based) is in the first place. Another major issue has to deal with the dearth of technical AI expertise in ocean sciences/engineering. And funding agencies do not understand the implication of using AI methods towards such stochastic domains where uncertainty can be tackled effectively using such methods."

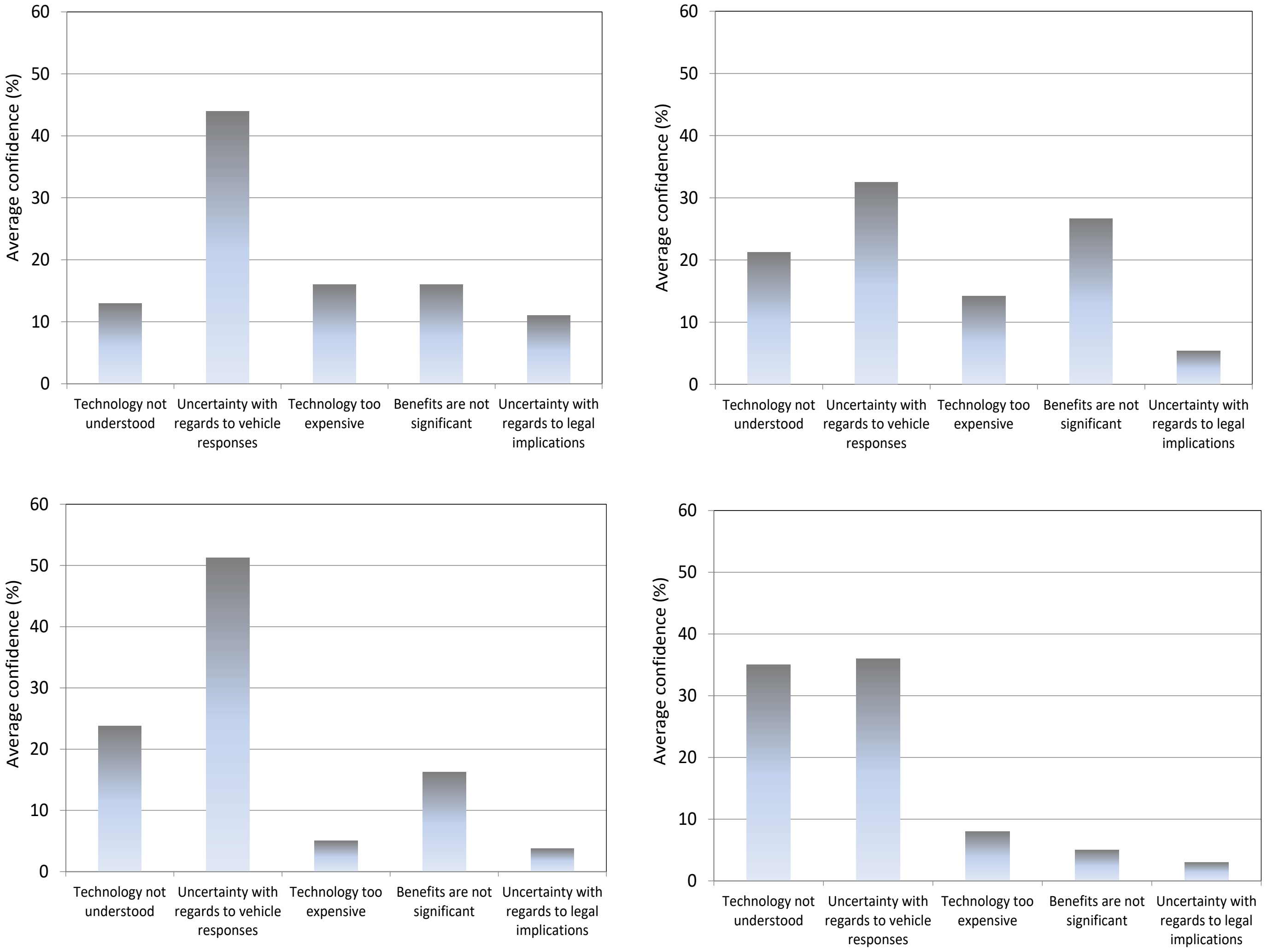

Fig. 5. Average of the assessments provided by managers (top left), technologists (top right), engineers (bottom left) and researchers/scientists (bottom right).

In the group formed by engineers all but one gave their highest assessment to uncertainty with regards to vehicle response. Expert 15 assigned 50% to both technology not understood and uncertainty with regards to vehicle response. Expert 22 commented: "… potential risks, either real or perceived, are the biggest roadblock." Expert 18 supported this view: "This applies to oceanographic use of autonomy, and in particular to relatively short missions, ~24 hours and less. The proposal mechanism [to secure funding] requires that scientists assume available technology, not developmental capabilities. They therefore have limited incentive to take risks [with respect to] autonomy. Why risk the delivery of a map, which can be generated using conventional pre-planned missions, if the map is what they need for their science? Part of the issue is cost of ship-time. It is too expensive to take unnecessary risks. Longer-term programs, especially those run from land, have more incentive to try autonomy and incur less risk."

Expert 1 shares the same view in the narrative, this expert commented: "There are so many diverse operating areas and mission goals, on a dive by dive basis, that to encompass every scenario into a mission planner, with success, may be impractical or with little benefit at this time."

For technologists the main cause for not adopting the technology is the uncertainty with regards to vehicle behavior, however, unlike other groups, this group identified as the second most likely explanation benefits not significant. In this group we find the greatest diversity in assessments, with one expert identifying benefits not significant as the main explanation, expert 3 assigned 80%, commenting: "1) AMP can/should be placed in a framework of 'hard' security rules that make the use of the technology safe for the vehicle. The issue then is to make it safe with respect to the end users' expected result; 2) the benefits potential for AMP is not significant for at least 75% of dives that are standard mapping patterns with various payloads. In most (our) cases systematic mapping is required in a given area, with emphasis on maximum/nominal data quality data. Perhaps we need key projects/examples for a cultural change? 3) AMP must be configured and specified for at least each new use case; standardized missions in the military field for example allow validation of behavior, in the variety of ocean science use cases the development loop is less easy to handle."

Expert 19 assigned 40% to both the technology is not understood and technology is too expensive, commenting: "From a commercial point of view, the value proposition may not be well defined and so the unknowns - which have to be solved using manpower and time - have an unknown value, thus cost > value."

Expert 4 states that "by far the biggest issue is trust", with the top cause for failure to adopt being uncertainty with regards to vehicle response.

The group formed by managers also identified uncertainty with regards to the vehicle response as the main cause for failure to adopt AMP systems. Expert 7 stating: “Adaptive mission planning algorithms are well established and reasonably well understood and the benefits, particularly for long missions can be significant. AUV operators, however, are reluctant to allow an expensive vehicle full freedom to determine its path plan and mission without retaining the human operator in the loop. Since it is difficult to keep continuous track of the vehicle, it is not so easy to let it do its own thing.” The other experts in this group present similar arguments. Expert 21 stating: “From my experience it is not perceived but sometimes actual failure to understand or be able to properly predict and modify behavior for vehicle response” and expert 6 agreed with this view: “The asset value is too significant, and the requirement for precise position prohibit true autonomy. Our use of AUV (mapping) necessitates great confidence in position.”

Expert 25 provides a clear example of the uncertainty associated with this assessment: “I split this between failure to understand the technology and lack of benefits. The dominating factor, however, is that operators are reluctant to let something operate in their space when they don't know where it is and they can't get immediate information about its position, especially when combined with complete lack of understanding of why it's out there and what benefit it will provide.”

2) Assessment analysis by years of experience

To assess whether or not the difference between groups of experts defined by years of experience were statistically significant we used the X^2 test, Table II.

TABLE II

P-VALUES FOR THE X^2 STATISTICAL SIGNIFICANCE TESTS FOR DIFFERENT YEARS OF EXPERIENCE

p-value	years of experience < 5	5 < years of experience < 10	10 < years of experience < 15	Greater than 15 years
years of experience < 5	-	0.286	0.152	0.625
5 < years of experience < 10	0.112	-	<0.005	0.580
10 < years of experience < 15	< 0.005	0.381	-	<0.005
Greater than 15 years	0.633	0.557	0.238	-

The X^2 test between 5 < years < 10 and 10 < years < 15 gives a p-value of 0.381 whist the reciprocal test gives a p-value < 0.005. An explanation is that for these two groups two experts provided a skewed distribution; experts 2 and expert 3 with assessments of 70% and 80% respectively to benefits are not significant.

Following an analysis of the statements provided by the experts, it is possible that some bias has been unconsciously introduced. Expert 2 stated: “This is a little tricky, since the use of adaptive planning schemes is highly mission dependent. In general, though, the limited survey horizon of on-board sensing limits the amount of meaningful adaptation that can be achieved. Also, the current state of the art in using data assimilating models is such that the physical scale of the models, relative to the observation scale of single AUV, is quite limited. I believe adaptive schemes have their place, but that place might be onshore, where they can coordinate large volumes of information from multiple heterogeneous assets, rather than embedded onto a compute- and sensing-constrained platform.”

Expert 2 assumed that the AUV would have to have real time access to a physical model of the environment. This approach is followed for some adaptive autonomous ocean sampling networks frameworks that have been developed and are also currently under development [35]. Expert 3, on the other hand, is arguably introducing bias based on his own experience of a particular subset of mission profiles, focusing on standard seabed mapping missions.

VII. ROOT CAUSE ANALYSIS

The root cause analysis concludes that insufficient demonstration trials is the most likely root cause for failure to adopt AMP, Table III. Benefits are not significant and technology too complex are the next two most likely root causes. These findings are different from those presented in [36]. In [36] the authors concluded that insufficient demonstration trials was the most likely cause for failure to adopt AMP at 26%, with lack of risk assessment at 14% the second most likely cause and technology not well explained at 13% the third. Here, with twenty-five rather than nine experts, if we consider the mean of all assessments, we conclude that lack of demonstration trials is the most likely root cause, Table III. However, this perception varies from one type of expert to another, depending on their role, Table IV, assessed below.

TABLE III

ASSESSMENTS FOR THE ROOT CAUSE FOR FAILURE TO ADOPT AMP BASED ON THE AVERAGE OF ALL ASSESSMENTS.

Root cause	Confidence (%)
Insufficient demonstration trials	23.69
Benefits are not significant	18.07
Technology too complex	12.35
No predefined lifecycle	8.23
Development costs not tangible	7.80
Lack of risk assessment documentation	7.37
Lack of probabilistic risk assessment	6.19
Uncertainty with regards to legal implications	5.78
Not explained properly	5.75
Technology not disseminated wide enough	4.78

A. Professional Role

The distributions obtained for different professional groups vary quite significantly for some hypotheses. All experts have identified insufficient demonstration trials in the top two most likely root causes. However, technologists and researchers/scientists selected insufficient demonstration trials as their second most likely root cause. For technologists, benefits are not significant is the most likely root cause while for researchers/scientists technology too complex is the most likely root cause.

The X^2 test takes into account the variance on all categories. Results of conducting the X^2 test on the assessments provided by different professional roles, Table V, show that differences between the assessments provided between researchers and technologists and researchers and engineers are statistically significant.

B. Experience

In terms of years of experience, the average of assessments provided by individuals with different years of experience are not statistically significant, Table VI. Differences between the average of the assessments provided for all root causes, for the group between 10 and 15 years experience is different from the average of assessments provided by the groups with less than 5 years and greater than 15 years, with a p-value lower than 0.005. As discussed earlier, this group contains experts 2 and 3. Their assessments may be biased towards the type of missions that they have carried out in the past – geological surveys. Therefore, the differences between different years of experience groups may not actually be statistically significant.

TABLE IV

ASSESSMENTS FOR THE ROOT CAUSE FOR FAILURE TO ADOPT AMP BASED ON THE AVERAGE OF ALL ASSESSMENTS FOR FOUR GROUPS: MANAGERS, TECHNOLOGISTS, ENGINEERS AND RESEARCHERS/SCIENTISTS. IN BOLD ARE THE TOP TWO MOST LIKELY ROOT CAUSES FOR EACH PROFESSIONAL GROUP.

Root cause	Manager	Technol.	Engineer	Researcher /Scientist
Technology not disseminated wide enough	3.1	5.59	4.45	9.17
Not explained properly	3.1	4.35	7.42	9.93
Technology too complex	6.86	11.3	11.9	**28.9**
Insufficient demonstration trials	**23.8**	**21.1**	**42.3**	**19.5**
Lack of risk assessment documentation	9.75	8.25	5.61	9.33
Lack of probabilistic risk assessment	10.52	3.13	3.36	7.12
Development costs not tangible	10.2	6.73	2.13	5.78
No predefined lifecycle	5.76	7.44	2.88	2.2
Benefits are not significant	**16**	**26.7**	**16.3**	5
Uncertainty with regards to legal implications	11	5.4	3.75	3

TABLE V

X^2 TEST ON THE AVERAGE OF THE ASSESSMENTS PROVIDED BY EACH PROFESSIONAL GROUP, FOR THE ROOT CAUSE FOR FAILURE TO ADOPT AMP.

P-value	Managers	Technol.	Engineers	Researchers
Managers	-	0.233	< 0.005	0.233
Technologists	0.695	-	0.0798	< 0.005
Engineers	0.0215	0.174	-	< 0.005
Researchers	< 0.005	<0.005	<0.005	-

TABLE VI

X^2 TEST ON AVERAGE OF ASSESSMENTS PROVIDED BY GROUPS BASED ON YEARS OF EXPERIENCE FOR ROOT CAUSE FOR FAILURE TO ADOPT AMP.

p-value	years of experience < 5	5 < years of experience < 10	10 < years of experience < 15	Greater than 15 years
years of experience < 5	-	0.372	< 0.005	0.988
5 < years of experience < 10	0.753	-	0.845	0.977
10 < years of experience < 15	< 0.005	0.956	-	0.006
Greater than 15 years	0.988	0.952	< 0.005	-

VIII. RECOMMENDATIONS FOR ENGINEERING MANAGEMENT

A. Demonstrations

From this study the lack of sufficient trials is by far the major factor hampering the more widespread adoption of adaptive mission planning software. Increasing the number of trial and demonstration deployments is an obvious recommendation to mitigate this.

Making the results of the trial deployments public and widely accessible are of equally great importance. One key point here is what makes a trial a successful test? Is it the identification of a given target or feature? Is it the time taken to find the target or the number of attempts? These criteria need to be defined before the AUV community starts discussing validation of the technology. Once criteria have been defined it becomes a question of identifying the number of successful tests to statistically quantify the confidence that a given criteria is met. To address this, one or more groups with well-established capability for AMP could offer to run missions with objectives and criteria set by groups not having that capability, as demonstrators applicable to a wider community. Such a set of actions will increase community confidence in the precision and reliability of AMP.

In planning demonstration missions the target audience should be crystal clear. A perceptive analysis of the pitfalls of introducing new high technology solutions [37] shows that while early adopters will seek to understand the technology, accept certain risks, and work with development teams, the early majority users will look first and foremost for improved productivity with easy integration into their business. For the early majority, the criteria will therefore include evidence of likely value added in various market segments, likely return on capital invested, and whether the technology is likely to be accepted by their own customers.

B. Risk

There are several strategies that one organization can adopt in order to manage risk. Mindfulness is a risk management strategy where one organization undergoes constant scrutiny of existing expectations [38]. The expectations are continuously refined based on new experiences. Anticipation risk management strategy implies that there is a good level of understanding of the problem. Here one organization favors precise identification of possible difficulties so that remedies can be designed and implemented prior to operation. Resilience favors mitigation instead of anticipation. Here organizations assume that they will be surprised, so they concentrate on developing general resources to cope and respond swiftly. Flexibility or slack is a risk management strategy whereby an organization has the ability to put in place other acceptable states. Flexibility is a measure of the number of number of acceptable states, their variety and utility, the consumable resources in reaching other states and the time conserved in reaching other states.

Autonomous underwater vehicle deployment risk is mostly managed by applying mindfulness. Deployments in extreme environments, such as under ice, tend to be supported with anticipation risk management strategies.

Early applications of AMPs are likely to be conducted in benign environments, such as open and coastal waters. For this technology the aim should be to promote innovation, therefore the goal should be to manage risk and not avoid it [39], therefore mindfulness and flexibility can be used to support the early deployment of this technology.

C. Training

Addressing the three main root causes in Table III of failure to adopt AMP requires professional development training covering the theoretical concepts, the practical implementation of those concepts, and hands-on experience on real vehicles at sea. The organizations best placed to deliver this type of training are those that combine research and development with extensive AUV deployment campaigns. Coincidently, a number of such organizations are developing new outreach programs to the wider user community. Examples include the Center for Marine Robotics at the Woods Hole Oceanographic Institution, USA, the Marine

Robotics Innovation Center, Southampton, UK and NATO's Center for Marine Research and Experimentation, Italy. Tutorial sessions and master-classes associated with conferences such as IEEE/MTS Oceans and IEEE AUV workshops could address training in the theory and implementation of AMP, but they rarely offer the hands-on, in-water experience this study shows is key.

D. Engaging the Early Adopters

The most important message to developers of AMP is that the early adopters are after a business or science goal and not a technology goal [37]. An effective way of finding out their needs and what drives their vision is to converse, build trust, and develop pilot projects to deliver the outcome-driven AMP missions forming their business vision, be their business scientific research, commerce or defense. This means fostering contact between early adopters and the engineers and researchers involved in AMP development in order to build a wider understanding, especially of the technical and business risks. Attempts to maintain contact only through business development staff are therefore likely to fail.

IX. LIMITATIONS

The aim of this paper is to identify why AMP is not used by the wider AUV community from the perspective of managers, engineers, technologists and researchers. It would benefit this field to explore the meaning of AMP as interpreted by the users. Exploring the semantic meaning, using lexicons in a componential analysis framework would allow us to assess if it is the meaning of the word and different elements of its functionality that is hindering the technology use [40]. In our research we approached mature users who have been exposed to AMPs and their capabilities.

One limitation of this study is that we did not use a technique such as Grounded theory to analyse the text provided by experts with their rationale for a given hypothesis [41]. Grounded theory is particularly useful if there is a substantial amount of written information about the topic and this theory would have allowed us to identify hypotheses from a systematic analysis of the text. However, with this theory it would have been difficult to establish the causal relationship in a hierarchical model, such as that presented in Figure 2.

Prior research has noted (e.g. [42]) that there are both techno-economic and organizational factors that influence technology adoption. To explore this question we would have had to have formulated an hypothesis related to the degree of general connection between the technology and the organization's existing operations [43], the technology specificity, the degree of urgency of the problem to which the technology is related, the quality of information received for using the technology, the top management interest and the organization climate [42]. In the study presented in [42] the authors analyzed seventy-three cases of technology transfer of NASA innovations. The questionnaires were submitted to individuals involved in these projects. Our research focused on a single technology: AMPs. This did not allow us to test organizational factors, but did allow us to test more detailed analyses such as how to establish the most likely root cause of failure to adopt AMP. We have established that the outcome varies, depending if the question is asked from a Manager, Engineer and Technologist or a Researcher.

We captured the most innovative characteristics published in the literature, such as complexity, costs, communicability, triability, profitability and observability factors [44][45][46]. We did not capture factors such as divisibility and social approval. Divisibility, this is "the extent to which an innovation can be tried on a small scale prior to adoption" [45] is important. The two AMPs that have been used most frequently for oceanographic research are MOOS-IvP and T-REX. Future research should explore if divisibility plays a role in AMP adoption.

To further explore the reasons for limited AMP usage on AUVs we sought perspective from scientists who have either used or intended to use AMPs directly in their work. We asked for comments on their experiences and their reflections on the reasons why the technology was not widely adopted. The scientists who have provided their views are not in the cohort of 25 experts used in this study. Scientist A, from the United States, was involved in the deployment where one out of 50 missions was conducted with AMP fully deployed. Scientist A stated that, "I believe it is an issue of funding. Funding agencies want the vehicles to be used for maximizing data collection and don't necessarily want to pay for autonomy even though that is really the next step in ocean sampling. Most of the compelling applications for autonomy are within scientific disciplines and not really the engineering per se. Funding agencies are slow to take risks to invest in not only the demonstration but also the routine use of autonomy." When asked to review the decision tree, Figure 2, Scientist A's comment was "I would not term the benefits as not significant but not understood. I think many do not understand the benefits of smart sampling and improving synoptic understanding of the environment. Even what we did was fairly specialized and for the community it will take some autonomy applied to some very basic measurement to convince that this is worth the investment and risk."

The perspective of Scientist B for not adopting AMP, (from Australia) are presented in Appendix II. Scientist B participated in AUV work where AMP was available for sea trials but it was not fully deployed, it was instead tested offline. When asked to comment on the decision tree of the root cause for failure to adopt AMP. Scientist B stated "Yes, I would agree that root cause 4 (Benefits are not significant) was the main obstacle and my points #1 and #2 align with this. I think to a lesser degree root cause 2 (Uncertainty with respect to vehicle response) was also a factor, the uncertainty with respect to vehicle response was seen as a risk - I touch on this in my third point."

Scientist C, (also from Australia), worked on developments that were focused toward AMP; however, a real-time deployment of AMP on AUVs was not realized in published work. Two points made by Scientist C were that AMP matches better with smaller, more affordable AUV assets. This speaks to the risk elements of AMP adoption. It might also explain the speed of AMP development. The cost of AMP computational hardware requirements is reducing over time and becoming more realizable on smaller AUV platforms that have more stringent power and mass requirements. A second point raised by Scientist C was that perhaps commercialization efforts have resulted in reduced publication exposure for AMP. As universities and research labs seek to partner with manufacturers on AMP development, they may withhold some or all of their AMP research due to commercial sensitivities.

Each of scientists A, B and C are qualified to PhD level, however Scientist A is predominately a science researcher and Scientists B and C are engineering researchers. Both A and B argue that lack of funding, which resonates with lack of trials, is the main root cause. However, as to second main root cause, Scientist

A argues that the Technology is not understood while Scientist B argues that the benefits are not significant. This is in line with our findings using 25 experts.

X. CONCLUSION

Our study shows that adaptive mission planning based control systems are not yet considered, by experts, to be sufficiently mature for use in operational AUVs. While our study has shown that users (here scientists and researchers) do recognize the substantial benefits that this technology can provide to subsea vehicle missions, AUV researchers, operators and managers need to place a higher priority on AMP development and introduction into open-water operations. However, there should be continuous engagement between AUV researchers and operators with users to ensure that the benefits are clear and become substantial.

It is recommended that more trials be undertaken with adaptive mission planning systems on AUVs. There are different solutions for AMP technology. It is inappropriate to treat all solutions as being the same. This study does not differentiate between different solutions, but recognizes that different solutions may have different degrees of success. These demonstrations should take into account the different types of users; demonstrations should be designed as effective reference cases for the particular target users. For example, when demonstrating to commercial early adopters the evidence for value added, potential markets should be presented alongside the technology. The outputs of the technology should be shown within the context of the end-to-end value chain, not just the data acquisition mission at sea.

The conclusions presented here are based on assessments provided by experts involved in AMP development or applications. We have not interviewed legal experts. The issue of national and international law pertaining to AUVs has become more prevalent in recent years. The legal community is currently dealing with AUVs as automated machines, with no intelligence. In this study, uncertainty with regards to legal implications was seen to be amongst the least important factors, by the experts, for failure to adopt AMP. This may be, perhaps, because there were no legal experts in this study. Their views should be considered in subsequent studies of this type.

APPENDIX I

TABLE A1

EXPERTS DETAILS

Expert	Years of experience	Employer type	General expert details
1	8	Research laboratory	An engineer in AUVs. Works for an oceanographic research institute in the United States.
2	13	Research laboratory	A senior engineer in AUVs. Works for an oceanographic research institute in the United States.
3	12	Government institution	A trained mechanical engineer with expertise in robotics. Conducted numerous AUV campaigns, mainly with large platforms. Works in France.
4	6	Research laboratory	A former University lecturer in robotics. Has many years experience in autonomy for space systems. Is currently a researcher for a private research institute.
5	15	Private company	An AUV operations manager and a pioneer of using AUVs within the private sector for bathymetry surveys. This expert is based in United States.
6	22	Other	A former University lecturer in oceanography. One of the pioneers in AUVs and on adaptive control and sampling. Currently an investigator and book editor. Based in the United states
7	5	Research laboratory	A Professor in geology and an AUV user. Uses large AUVs that are operated for geological survey. Based in Germany.
8	12	Private company	A principal research scientist in field robotics. Has developed several AUV systems and has published numerous AUV related scientific papers. Based in Australia.
9	2	Private company	An AUV manager with a background in electrical engineering, previously worked for many years in the military sector.
10	2	Research laboratory	A researcher and PhD student. Developer of adaptive control algorithms for AUVs. Based in India.
11	7	Government institution	A director of a university center for marine engineering control. Based in Australia
12	4	Private company	An AUV user and systems developer with significant experience in AUV deployments. Based in the United States.
13	15	Defense Research Laboratory	A principal engineer in autonomous underwater vehicles. Based in Norway.
14	20	Government institution	A Professor in systems control with research interests in control and communication systems for marine AUVs. Head of a research laboratory that owns several autonomous vehicles and supports the research of several students.
15	14	Government institution	A Professor in marine engineering, AUV user and developer. Based in Australia.
16	12	Private company	Experienced robotics engineer and manager with background in AI. Based in Canada.
17	12	Research laboratory	A research engineer with a PhD in mission adaptive technology for AUVs. Has participated in more than 10 AUV supported science campaigns. Based in the United States.
18	7	Research laboratory	A senior research engineer at a research laboratory as head of a research group responsible for development of mission adaptive technology tailored for large AUVs. Based in the United States.
19	6	Private company	A consultant in AUVs, has worked on high profile AUV deployments, including the deployment of the ISE Explorer in the Arctic. Based in New Zealand.

TABLE A1 CONTINUATION

Expert	Years of experience	Employer type	General expert details
20	9	Research laboratory	University Professor and research scientist for a British Marine Research Centre. AUV user. Based in Scotland.
21	5	Research laboratory	Director of a large research center for coastal & ocean mapping. Has background is marine geology and is an AUV user. Based in the United States.
22	3	Research laboratory	Conducted many AUV deployments and is leading the design of a new AUV for a Canadian University.
23	6	Private company	An AUV survey supervisor. Has a background in marine geology. Based in the United States.
24	10	Other	A professor in marine geology, works for an academic institution. Based in the United States.
25	10	Government institution	A senior researcher and director of a research institute in ocean research. Researches algorithms for autonomous mission planning.

APPENDIX II – SCIENTIST B MAIN ROOT CAUSES FOR FAILURE TO ADOPT AMPS

1. Advanced decision making was not a stakeholder interest. The sponsors for a lot of the work were from the marine science sector, they were happy enough with a regular grid survey of the benthos. Accurate geo-referenced positioning, reliability and acquisition of good imagery were seen as priorities.

2. Immediate benefits of autonomous decision making were not seen as significant for the cases we had at the time. While advanced decision making could potentially have reduced the duration and increased the effectiveness of AUV missions, in the context of a complete field trip cycle (including preparation and logistics, steaming long distances to a site, launch and recovery) the actual time in the water of the AUV was not a huge bottleneck. Note that we were only doing a relatively small number of dives with Sirius per year, the benefits would be far more compelling if AUV use was more routine, if a fleet of vehicles were used, or for vehicles of long endurance.

3. Implementation is difficult. There were a couple of computationally expensive steps in the algorithm, these could probably have been overcome (and certainly could now with modern hardware). However ship time to run pure engineering trials was rare. Typically if we were on board a vessel the main objective was to gather a dataset for some stakeholder, and so there would be a lot of risk involved in trying out a developmental algorithm that would send the vehicle on an unknown path.

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